Households in Motion:
Co-location Frictions and Gender Inequality

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Abstract

This paper studies how co-location frictions—constraints that arise when accepting a job in another location induces job interruptions for the spouse—shape migration decisions and contribute to gender inequality in the labor market. Using data on displaced workers, I show that household migration responses are almost three times larger after a husband's job loss than after a wife's. Movers experience smaller earnings losses than stayers, but these gains accrue disproportionately to men, widening gender gaps. To quantify the effect of co-location frictions, I develop and estimate a two-location household search model that incorporates spatial search frictions, gender-specific offer distributions and arrival rates, and unequal weighting of spousal earnings. The estimates imply that co-location frictions account for roughly half of the gender employment gap and 8.6 percent of the gender wage gap for dual-earner couples. Counterfactual simulations highlight that expanding access to remote work relaxes these constraints and reduces gender gaps in both employment and wages.

Keywords: Household search, co-location frictions, geographic mobility, gender gap

JEL Codes: J16, J61, J64, J65

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1 Introduction

Gender inequality remains a persistent feature of modern labor markets. Despite substantial gains in women's labor force participation and the narrowing of the gender wage gap over the twentieth century, large disparities in employment and earnings endure. For every dollar earned by men, women still earn about 83 cents (Goldin, 2024). Traditional explanations emphasize differences in human capital and experience (Blau and Kahn, 2017), while more recent work highlights household decisions such as childbearing and the resulting "child penalties" (Kleven et al., 2019). A growing body of evidence also points to the importance of locations in shaping careers and earnings trajectories (Fadlon et al., 2024; Card et al., 2025). As dual-earner households have become increasingly prevalent, within-household trade-offs related to geographic mobility have emerged as a critical but underexplored source of persistent gender inequality.

This paper examines how co-location frictions—constraints that arise when accepting a job in another location induces job interruptions for the spouse—shape migration decisions and contribute to gender disparities in employment and wages. When labor market prospects are geographically misaligned, relocation may increase total household income but worsen outcomes for one partner (Mincer, 1978). Yet identifying the gendered impact of co-location frictions is challenging. Migration decisions are made jointly within households and occur at discrete moments, such as following job changes. Observed earnings patterns after migration can be difficult to interpret: a rise in the husband's earnings and a decline in the wife's earnings after a move could reflect a deliberate trade-off favoring the husband's career or an optimal response to differing outside options.

I address these challenges by combining new empirical evidence on migration following job displacement with a structural model of household job search. Job displacements that arise from plausibly exogenous events offer a credible setting for studying household migration. Using these shocks as quasi-experimental triggers, I show that co-location frictions weigh more heavily on married women than on married men, and that migration disproportionately benefits men. The structural model embeds migration costs, gender heterogeneity in job opportunities, and unequal weighting of spousal income, allowing me to isolate the contribution of co-location frictions from other gender-based differences. Quantitatively, these frictions emerge as an important driver of persistent gender gaps in employment and earnings.

The analysis proceeds in four steps. First, using data from the Current Population Survey's Displaced Worker Supplement (DWS), I document migration responses and post-displacement labor market outcomes. Among heterosexual married couples, household migration responses are nearly three times higher after a husband's job loss than after a wife's. Following job displacement, married men move at similar rates as single men, whereas married women are substantially less mobile than single women. Under the assumption that married and single workers of the same gender face similar labor markets, this pattern suggests that co-location frictions bind more strongly for women. The asymmetry persists even after controlling for pre-displacement earnings shares, indicating that households may place unequal weights on male and female earnings when making migration decisions. Movers experience smaller earnings losses after job loss than stayers, but the gains accrue disproportionately to men. Female trailing spouses experience persistent declines in employment and wages, whereas male trailing spouses recover quickly. Together, these findings reveal that co-location frictions impose large costs on women's careers and reinforce gender inequality within households.

Second, to interpret these patterns and quantify the underlying mechanisms, I develop a two-location household search model that extends Guler, Guvenen, and Violante (2012) to incorporate migration costs, unequal valuation of spousal earnings, and gender-specific labor market heterogeneity (e.g. offer arrival rates, offer distributions), thus reflecting both demand side (labor market opportunities) and supply side (within-household discounting) forces. Compared to a single-worker model, it is known that household search introduces new opportunities, such as the "breadwinner cycle" in which spouses alternate as the primary earner to climb up the job ladder. A new trade-off emerges due to offers from outside the current location: accepting such an offer requires the spouse to quit their job, generating co-location frictions. Each spouse's optimal job search strategy, which is characterized by a set of reservation wages, depends on their partner's employment status and wages and on the location of the new job, making labor transitions inherently interdependent.

Third, I estimate the model using the Method of Moments, targeting moments from the DWS. I assume that married and single individuals of the same gender face the same wage offer distributions, allowing differences in arrival rates, destruction rates, and migration costs to capture household-level effects. The estimated male offer distribution first-order stochastically dominates the female distribution, consistent with demand-side differences. Married men receive more frequent job offers than single men, while married women receive fewer than single women, consistent with intra-household specialization in search effort (Pilossoph and Wee, 2021). Compared to inside offers, outside offers arrive at a much lower rate, but they affect workers through a direct effect that opens up more job opportunities as well as an indirect effect that hurts the trailing spouses. Estimates of intra-household weighting imply that women's earnings are valued at roughly 63 percent of men's when couples make joint decisions. The model successfully replicates the empirical patterns in migration and post-displacement earnings for both displaced workers and their spouses.

Finally, I use the model to quantify how co-location frictions and related mechanisms contribute to observed gender gaps. Because women are more likely to be "tied movers" and "tied stayers", geographic constraints disproportionately depress their employment and earnings. Household co-location frictions explain roughly half of the 3.3 percentage-point gender employment gap and 8.6 percent of the 35.8 log-point gender wage gap. Gender differences in labor market frictions explain 21 percent of the wage gap, while unequal weighting of spousal income accounts for about 5 percent. I also examine the role of remote work, modeled as outside offers that do not require relocation. Remote work reduces migration but increases overall employment, especially for women, narrowing the gender gap in employment and wages.

Taken together, these findings underscore the importance of household-level constraints in shaping both geographic mobility and labor market inequality. Policies that reduce co-location frictions, such as expanding remote work options or improving access to child care, can facilitate more equitable labor market transitions and improve outcomes for dual-earner households.

Related Literature. - My paper contributes to four strands of literature.

First, I contribute to the large literature on understanding the gender pay gap. Traditional human capital explanations have lost explanatory power over time as women' education attainment and work experience caught up to men's, with attention shifting toward occupational, industry, and firm-level segregation (Blau and Kahn, 2017), child penalties (Kleven et al., 2019), gender norms (Bertrand et al., 2015, 2021), and job search behavior (Cortés et al., 2023). Fadlon et al. (2024) show that poor initial labor market conditions widen the gender pay gap through a family–career trade-off channel, with women less likely to move for better jobs. This paper quantifies how co-location frictions contribute to persistent gender inequality in earnings.

Second, my paper advances research on family migration and labor market outcomes. Prior studies have found mixed effects of migration on women's labor market outcomes and household earnings (Cooke et al., 2009; Blackburn, 2010; Burke and Miller, 2018). Venator (2024) shows that unemployment insurance for trailing spouses increases both migration and post-move earnings for women. Other studies highlight the unequal weighting of women's earnings in migration decisions (Foged, 2016; Jayachandran et al., 2024). I build on this literature in four ways. First, I establish clear evidence of gender-asymmetric mobility at the moment of job loss, distinguishing between gender effects (differences in men's and women's labor market opportunities) and household effects (co-location frictions). Second, I measure both the initiating spouse's gains and the trailing spouse's losses within the same household when responding to labor market shocks. Third, I provide joint empirical and structural evidence that households place lower weight on women's earnings when making migration decisions. Finally, I develop a structural model with richer gender heterogeneity—such as differences in offer arrival rates—that allows a full decomposition of the sources of observed inequality.

Third, my model extends the theoretical work in joint search with multiple locations developed by Guler et al. (2012). Later work building on this framework includes Braun et al. (2021) and Rueda and Wilemme (2025). While Braun et al. (2021) explore how converging male–female opportunities contributed to the declining migration rates, I address the reverse question: how much do co-location frictions sustain gender inequality? Rueda and Wilemme (2025) examines career switches among highly educated, high-earning couples; my model places more emphasis on migration and incorporates richer gender heterogeneity and unequal weighting of spousal incomes, which are crucial for disentangling co-location frictions from other demand side and supply side factors. Other related work includes non-cooperative household models of mobility, wage growth, and marital stability (Gemici, 2023), and directed-search frameworks that consider welfare implications of household migration with local amenities (Foerster and Ulbricht, 2023).

Finally, I contribute to the literature on the cost of job loss. Previous research has documented large and persistent earnings losses following displacement (Jacobson et al., 1993; Davis and Von Wachter, 2011; Farber, 2015), but relatively few studies examine gender differences. Illing et al. (2024) show that women face larger earnings penalties than men in Germany, especially in households with young children. Using U.S. data, I document similar gender disparities and highlight geographic mobility as a key mechanism behind these differences.

The remainder of the paper is organized as follows. Section 2 describes the data and the empirical strategy. Section 3 presents the empirical findings from both the individual-level and household-level analyses. Section 4 introduces the household search model. Section 5 discusses identification and reports the estimated parameters. Section 6 uses the estimated model to conduct counterfactual analysis. Section 7 concludes.

2 Data and Empirical Strategy

Identifying the effects of co-location frictions is challenging because migration is a choice affected by both labor market and non-labor factors. To address these challenges, I draw on the Displaced Worker Supplement (DWS) of the Current Population Survey (CPS), which provides plausibly exogenous job separations that allow me to examine how couples respond to male and female labor market shocks and how these responses shape subsequent labor market outcomes.

2.1 Data

The DWS is a biennial supplement to the CPS Basic Monthly Survey, fielded in January or February from 1984 to 2020. Following standard practice (Farber, 2015; Huckfeldt, 2022), I define displaced workers as those who report losing a job because their plant or company closed or relocated, because of slack work, or because their position or shift was abolished. These "big three" reasons largely reflect firm-level shocks rather than separations due to individual performance.

Geographic mobility is measured using the DWS retrospective question "Did you move to a different city or county after job loss?", and if so, whether the move was "because of job loss". I classify all city or county moves following job loss as "migrations" regardless of stated reason, to capture the full extent of geographic mobility.[1] The analysis is restricted to individuals aged 25–60, excluding the self-employed and unpaid family workers. Unlike much of the prior literature, I retain both full-time and part-time workers, since part-time employment is particularly common among displaced women.[2]

I also combine two other parts of the CPS to measure labor market outcomes of the spouses of the displaced workers: The March Supplement provides earnings information in the previous calendar year, while the Outgoing Rotation Groups (ORG) of the Basic Monthly files provide earnings at the time of the survey.[3]

2.2 Propensity Score Matching

In the absence of frictions, displaced workers could be expected to relocate quickly to areas with better job opportunities. In practice, migration involves trade-offs: moving may facilitate faster reemployment but also entails significant costs, such as established local networks or cost for finding new houses.

To isolate the causal effect of displacement on migration, I compare displaced workers

[1] Among displaced movers, 77 percent reported moving because of job loss. The remainder may have relocated for spousal or family reasons.

[2] Focusing on only full-time workers gives quantitatively similar results.

[3] For the Basic Monthly Survey, respondents participate for 4 months (survey months 1-4), out for 8 months, and then participate again for 4 months (survey months 5-8). Individuals in their 4th and 8th survey months are asked additional questions related to earnings and hours worked.

with observationally similar non-displaced workers. The combined March supplement and ORG allow me to construct such a control group and account for common migration trends unrelated to displacement. To align with the DWS, I define "long-distance migration" as moves across counties or states, excluding moves from abroad and within-county relocations.[4] I further restrict the control group to individuals with no unemployment spells in the prior year to reduce contamination from misclassified displaced workers.

Two challenges arise when using this dataset. First, displaced workers in the DWS report job loss up to three years before the survey, whereas non-displaced workers in the March Supplement report outcomes over only the previous year. For consistency in timing, I restrict the displaced sample to those who lost their jobs within one year before the survey.[5] Second, displaced and non-displaced workers may differ in ways that affect both migration and labor-market outcomes. To address this, I construct the control group using a Propensity-Score Matching (PSM) approach (Heckman et al., 1997). Specifically, I match exactly within cells defined by eight five-year time intervals (covering 1980–2020), one-digit industry codes at displacement (or the prior year's industry for non-displaced workers), gender, and marital status. Within each cell, I estimate propensity scores based on weekly earnings in the previous year, full-time status, age, and education. For the household-level analysis, I also match the spouse's earnings share in year $t-1$, which proxies for relative earnings power within the household. Each displaced worker is assigned two non-displaced controls with the closest propensity scores, without replacement.[6] This procedure yields well-balanced treatment and control samples (Table A2).

2.3 Summary Statistics

Table 1 presents summary statistics of selected variables for displaced workers by gender and marital status. Married workers are older, more likely to have children, and earned higher pre-displacement wages than singles, with especially large differences among men. Married men earned an average of $761 per week before displacement compared with $603 for single men. Among women, the married–single wage gap is narrower, and after displacement, married women's current wages conditional on reemployment even fall below those of single women. Married women are also less likely to to be reemployed or regain full-time work, highlighting that displacement is especially costly for them.

[4] Based on post-1999 migration-reason codes, more than 40 percent of cross-county moves are job-related, compared to only 12 percent of within-county moves.

[5] Relative to those displaced two to three years earlier, recently displaced workers have similar demographic characteristics but slightly lower average pre- and post-displacement wages.

[6] Results are similar under 1-to-1 matching but slightly less precise.

Table 1: Summary Statistics of Displaced Workers by Gender and by Marital Status

	(1) Married Men	(2) Married Women	(3) Single Men	(4) Single Women
Panel A: Demographics				
Average Age	40.95	40.89	36.98	39.33
	(9.68)	(9.65)	(9.65)	(10.08)
Share College Degree	0.23	0.25	0.21	0.23
	(0.42)	(0.43)	(0.41)	(0.42)
Share with Children	0.72	0.67	0.16	0.47
	(0.45)	(0.47)	(0.37)	(0.50)
Share White	0.88	0.88	0.82	0.78
	(0.32)	(0.33)	(0.39)	(0.41)
Panel B: Lost Job				
Weekly Wages - Lost Job (100USD)	7.61	4.83	6.03	4.74
	(4.79)	(3.64)	(4.11)	(3.56)
Lost Job Full-Time	0.95	0.76	0.90	0.82
	(0.22)	(0.43)	(0.30)	(0.39)
Job Tenure	6.19	5.53	4.50	4.54
	(10.53)	(9.33)	(10.00)	(9.12)
Panel C: Current Status				
Weekly Wages - Survey Date (100USD)	6.85	4.38	5.36	4.42
	(4.68)	(3.51)	(3.85)	(3.41)
Share Reemployed	0.61	0.52	0.52	0.56
	(0.49)	(0.50)	(0.50)	(0.50)
Share Full-Time Job	0.45	0.30	0.36	0.37
	(0.50)	(0.46)	(0.48)	(0.48)
Share Moved - All Reasons	0.09	0.05	0.12	0.09
	(0.29)	(0.23)	(0.33)	(0.29)
Share Moved Because of Job Loss	0.08	0.04	0.10	0.06
	(0.27)	(0.18)	(0.29)	(0.24)
Observations	7125	4720	4233	4055

Notes: CPS DWS 1982-2020. This table presents the mean and standard deviations (in parenthesis) of selected demographic variables and labor market outcomes. The sample includes individuals aged 25 to 60 who are not currently in school. Displaced workers are those that lost their jobs due to exogenous reasons within three years prior to each survey. Earnings are adjusted using CPI to 1999 dollars. “All Reasons” include both moves because of job loss and moves not because of job loss.

Patterns of geographic mobility reveal similar disparities. Married women are the least likely to move after job loss: only about 5 percent relocate, compared with 9 percent of single women. Married men also move less frequently than single men. The share of workers who report moving specifically because of job loss follows the same pattern.

One possible explanation for married women moving less after displacement is occupational sorting. Women are concentrated in occupations such as teaching, nursing, and administrative support, which are widely available across locations and thus less likely to require migration (Benson, 2015). Figure 1 shows the occupational distribution of displaced workers in their previous job, by gender (blue for men and red for women) and marital status (dark for married and light for single). Women are overrepresented in administrative support, while men are disproportionately displaced from geographically concentrated manufacturing jobs. Macaluso (2023) shows that the dissimilarity between the skill profiles of a worker's last job and all other jobs in a local labor market, termed local skill remoteness, shapes mobility decisions. If men are more likely to face high skill remoteness, they will also be more likely to move after job loss.

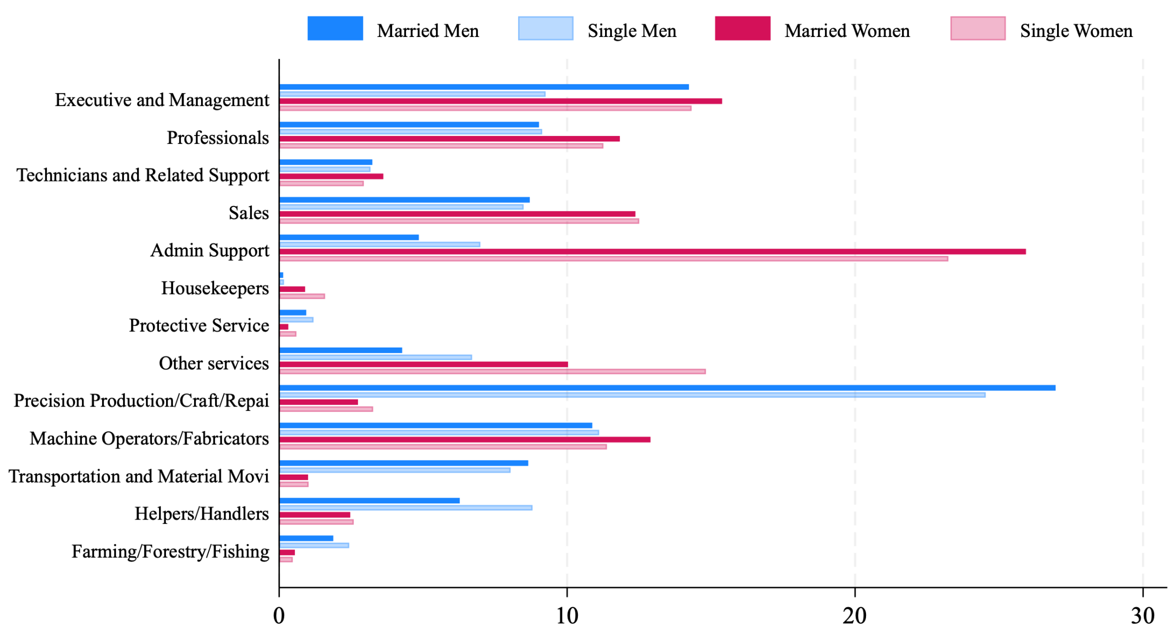


Figure 1: Share of Displaced Workers in Each Occupation Category

Notes: Occupations are divided into 13 broad groups. This figure shows the occupational composition of displaced workers in their lost job, separated by gender and marital status. The dark blue bar represents married male workers, the dark pink bar for married female workers, light blue for single male workers, and the light pink for single female workers. Each bar represents the share among a specific group of workers that were working in that occupation group.

However, occupation-based explanations alone cannot account for the gender gap. If women simply faced greater local demand, we would expect them to be reemployed more quickly than men. This holds for single women, who experience shorter unemployment spells than single men, but not for married women, who have the longest unemployment durations. Figure A1 presents Kaplan Meier survival estimates by gender and marital status for the displaced workers. At any unemployment duration, single women have the highest probability of exiting unemployment, consistent with stronger local demand, but married women have the lowest. These patterns suggest that supply side factors such as household constraints amplify gender inequality following displacement.

2.4 Empirical Strategy

Probability of Moving after Job Loss. To examine the effect of job displacement on mobility, I estimate the following model separately for men and women:

$$Moved_{i(t)} = \sum_{k \in \mathcal{K}} \mathbb{1}\{Married_{i(t)} = k\} * [\alpha_{0k} + \alpha_{1k} Displaced_{i(t)} + \Gamma_k X_{i(t)} + \theta_{tk} + \lambda_{sk}] + u_{it} \quad (1)$$

where $Moved_{i(t)}$ indicates whether worker i moved to a different city or county between $t-1$ and t. Set $\mathcal{K} = \{1\}$ or $\{0,1\}$, depending on whether the model is estimated on only married sample or on the pooled sample of married and unmarried workers. $Displaced_{i(t)}$ equals 1 if worker i experienced job loss in year $t-1$. $X_{i(t)}$ includes age, age squared, college degree, race (nonwhite indicator), presence of children, public-sector employment, as well as industry and occupation dummies.[7]

The key coefficient α_{1k} measures the effect of displacement on migration for workers with marital status k. The specification allows single workers of each gender to serve as controls for married workers of the same gender, under the assumption that they face similar labor-market conditions. As shown in Figure 1, married and single workers within gender indeed have similar occupational distributions. The specification also includes year fixed effects θ_t and state-of-residence fixed effects (λ_s), both interacted with marital status k. u_{it} is a common individual level i.i.d error term regardless of marital status, which assumes that conditional on observables, unobserved heterogeneity between married and unmarried workers do not correlate with their displacement status. Selection on unobservables into marriages, such as risk preferences that correlate with mobility, would bias results only if such traits differ systematically by gender. Standard errors are clustered at the matched pair level.

[7] While PSM was implemented within cells defined by 10 industry groups and other variables, here I control for more granular classifications with 17 industry groups and 13 occupation groups, with the latter as defined in Figure 1.

Identification relies on the assumption that, apart from job displacement, no other factor systematically affects the migration probabilities of displaced and non-displaced workers in different ways. Concerns about reverse causality (for example, workers quitting in anticipation of moving) are mitigated by defining displacement strictly as involuntary separations due to firm-level shocks and by matching displaced workers to observationally similar non-displaced controls. As migration often takes time, restricting the window to one year likely understates the full mobility response. Thus, these estimates should be interpreted as a lower bound on displacement-induced migration.

Labor Market Outcomes by Moving Status. To examine how migration mediates post-displacement outcomes, I estimate the following model separately for each gender:

$$Y_{i(t)} = \alpha_0 + \alpha_1 Displaced_{i(t)} + \alpha_2 Displaced_{i(t)} \times Moved_{i(t)} + \alpha_3 Moved_{i(t)} + \Gamma X_{i(t)} + u_{it} \quad (2)$$

where $Y_{i(t)}$ represents the outcome of interest: weekly earnings, employment status, or log wages. The coefficient α_1 captures the effect of job loss for those who did not move (stayers), α_2 represents gains from moving for displaced workers, and α_3 measures changes in outcomes for non-displaced movers. Because migration is endogenous, these estimates are descriptive, but they provide insight into how migration interacts with job loss to shape gender-specific outcomes and inform the structural model by indicating the relative importance of supply- and demand-side mechanisms.

3 Results on Migration and Post-Displacement Outcomes

This section presents the empirical findings on how job displacement affects migration (Equation 1) and subsequent labor-market outcomes (Equation 2). I show that households respond asymmetrically to male and female job loss and that this asymmetry widens the gender wage gap following displacement.

3.1 Individual Level Analysis

3.1.1 Probability of moving

Table 2 reveals a stark gender difference in migration responses to job displacement. Column 1-2 report estimates from Equation (1) for married workers only. Household migration response is 2.8 times larger after the husband's job loss than after the wife's. For married men, displacement raises the migration probability by 4.7 percentage points (p.p.); for married women, the effect is only 1.7 p.p. Relative to the baseline annual migration rates of 4.3 percent (male-displaced) and 3.5 percent (female-displaced) among controls, these effects represent increases of 109 percent and 50 percent, respectively.

Comparing married and unmarried workers further highlights the role of household co-location frictions (Table 2, columns 3–6).[8] Among unmarried individuals, migration responses are more similar by gender: displacement increases mobility by 4.9 p.p. for men and 3.8 p.p. for women. In contrast, marriage sharply reduces women's mobility: married women are 2.1 p.p. less likely to move than unmarried women, while no difference appears for men. Under the assumption that married and unmarried workers of the same gender face similar labor markets, this finding suggests that household constraints disproportionately limit women's mobility.

Table 2: Probability of Migration After Job Loss

	Married		Married+Unmarried		Married+NeverMarried	
	(1)	(2)	(3)	(4)	(5)	(6)
Gender of DW	Female	Male	Female	Male	Female	Male
Displaced	0.017***	0.047***	0.038***	0.049***	0.042***	0.052***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.010)	(0.008)
Displaced*Married			-0.021***	-0.002	-0.025**	-0.005
			(0.007)	(0.008)	(0.011)	(0.009)
Control Mean	0.035	0.043	0.046	0.053	0.044	0.051
Covariates	✓	✓	✓	✓	✓	✓
N	14154	21368	26310	34064	19571	29231

Notes: CPS DWS and March Supplement 1982-2020. This table reports coefficients from estimating Equation (1) with indicator for having moved across county or city as the outcome variable. "DW" refer to the displaced worker. Columns 1-2 are estimated on married samples, and columns 3-6 are estimated on both married and unmarried workers. Control mean reports mean annual migration rate for the non-displaced control group. Covariates include age, age squared, indicators for race, college, and children; weekly wages, full-time status, public sector indicator, and industry and occupation dummies for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Standard errors are clustered at the matched pair level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Divorce or separation could mechanically raise mobility among unmarried workers. Focusing on never-married versus married in columns 5-6 provides a comparison free from divorced/widowed cases. The results reinforce the point: Married women are 2.5 p.p. less likely to move than never-married women following displacement, while no such effect is observed for married men. Therefore, the asymmetric response is unlikely

[8] "Unmarried" includes those that are never married, separated, divorced, and widowed. It is used interchangeably with "single". Among all unmarried workers, 53% are never married individuals.

to be explained by a higher share of divorced or widowed women. The rest of the analysis will continue with the sample in columns 3-4.

By education group. College graduates are generally more mobile than non-college workers, reflecting either higher returns to migration (Amior, 2019) or smaller losses from local shocks (Notowidigdo, 2020). Columns (1)–(4) of Table 3 show that the married–single gap in migration among non-college workers is concentrated among women: married women are 1.9 p.p. less likely to move than single women, while men show no difference. Among college graduates, both men and women exhibit large married–single gaps. Despite being highly mobile, college-educated couples are more likely to reside in large cities with more job opportunities, making them less likely to move after job loss (Costa and Kahn, 2000; Compton and Pollak, 2007). Besides, co-location frictions may be especially costly for higher-skilled households, where forgone opportunities are greater.

Table 3: Probability of Migration After Job Loss - By Education Group and Children

	College		No College		No Child		Have Children	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	F	M	F	M	F	M	F	M
Displaced	0.057***	0.101***	0.032***	0.038***	0.055***	0.053***	0.020***	0.030**
	(0.015)	(0.016)	(0.006)	(0.007)	(0.009)	(0.007)	(0.008)	(0.015)
Displaced*Married	-0.030*	-0.048***	-0.019**	0.008	-0.029**	-0.003	-0.008	0.015
	(0.018)	(0.018)	(0.008)	(0.008)	(0.012)	(0.011)	(0.009)	(0.016)
Control Mean	0.059	0.068	0.042	0.049	0.056	0.065	0.038	0.043
Covariates	✓	✓	✓	✓	✓	✓	✓	✓
N	6123	7722	20187	26341	11321	16558	14989	17506

Notes: CPS DWS and March Supplement 1982-2020. Sample of both married and unmarried workers. "F" stands for female and "M" stands for male, which represent genders of the displaced worker. Control mean reports mean annual migration rate for the non-displaced control group. Covariates include age, age squared, indicators for race, college, and children; weekly wages, full-time status, public sector indicator, and industry and occupation dummies for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Standard errors are clustered at the matched pair level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

By presence of children. Children influence household migration decisions through both economic and non-economic channels. On the one hand, households with young children may be more willing to relocate in pursuit of higher wages that compensate for childcare costs. On the other hand, young children require substantial caregiving, which can reduce the ability of a displaced worker to search for distant jobs or relocate. Columns 5-6 of Table 3 show that among childless households, married women remain significantly less likely to move after displacement than single women. Among households with children (columns 7-8), however, married and unmarried workers move at a similar rate regardless of gender. This effect is driven by a large reduction in the probability of moving of unmarried parents, who likely rely heavily on local family and childcare networks and have less liquidity to finance a move after labor market shocks.

By age and time. Younger workers are more geographically mobile than older workers, but columns 1–4 of Table A4 show that married women are significantly less likely to move than unmarried women for both young and middle age group (25–40) and the older group (41–60), while men show no such difference. Household constraints on female mobility therefore emerge early in the lifecycle and are not limited to older couples. This also aligns with the findings in Goldin et al. (2017) that the gender earnings gap is expanding over the lifecycle. Female labor force participation and earnings relative to men experienced large increases between 1970-2000, and then plateaued after the 2000s. The gender differences also remains remarkably stable over time despite major shifts in women's labor force participation and relative earnings (columns 5–8).

3.1.2 Labor market outcomes by moving status

The results above show that men and women differ sharply in migration responses to displacement. This subsection examines whether migration mitigates the earnings and employment costs of job loss and whether these gains differ by gender based on Equation (2). Because detailed wage variables are available only from 1990 onward, the analysis covers 1990–2020.

Earnings. Table 4 shows that job displacement leads to large earnings losses for both genders. On average, displaced married women lose $238 per week (48% of pre-displacement earnings), while displaced married men lose $310 (39.5%). Migration partially offsets these losses but more substantially for men. Moving reduces the earnings cost by $198.5 for married men and $76.5 for married women, corresponding to 61% and 32% smaller declines, respectively, relative to stayers. Among unmarried workers, the moving premium is smaller and more similar across genders. These results suggest that migration facilitates earnings recovery, but primarily for married men.

Non-displaced workers who move experience declines in earnings relative to non-displaced stayers, suggesting that such moves are less likely to be job-driven. This pattern underscores the value of focusing on displacement-induced moves, where migration is plausibly triggered by employment opportunities rather than lifestyle considerations.

Table 4: Changes in Raw Weekly Wages After Job Loss

	Married				Unmarried	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Displaced	-238.3***	-310.4***	-241.0***	-324.6***	-220.5***	-299.3***
	(6.9)	(8.4)	(7.0)	(8.7)	(7.6)	(9.0)
Displaced*Moved			76.5**	198.5***	71.7***	63.4**
			(38.6)	(34.8)	(25.7)	(29.9)
Moved			-73.0***	-50.0**	-51.2***	-9.2
			(21.6)	(21.4)	(13.8)	(18.3)
Control Mean	499.9	785.7	499.9	785.7	483.2	599.1
Covariates	✓	✓	✓	✓	✓	✓
N	11473	16371	11473	16371	10289	10436

Notes: CPS DWS and March Supplement 1990-2020. Raw weekly earnings include zeroes for individuals who remain unemployed. Column 1-4 are estimated on the married sample, and column 5-6 are on the unmarried sample. “Female” and “Male” refer to the gender of the displaced worker. Covariates include age, age squared, indicators for race, college, and children; weekly wages, full-time status, public sector indicator, and industry and occupation dummies for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Standard errors are clustered at the matched pair level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Employment and wages. Table 5 decomposes these effects. Consistent with earnings patterns, women lose more relative to their previous wages and gain less from moving than men (wage ratio in columns 1–2).

The gender gap in moving gains reflects differences along both the extensive and intensive margins. Displacement sharply reduces employment, but men, particularly male movers, are much more likely to find new jobs (columns 3-4). Conditional on employment, moving is associated with a significant 7.6 p.p. wage gain for men and an insignificant positive effect for women (columns 5-6). These findings highlight the role of geographic mobility in facilitating reemployment and wage recovery, while also revealing that men benefit more from such mobility.

Gender differences in post-move outcomes may reflect differences in how well reemployment jobs match prior skills. Table A6 examines the likelihood of switching occupation (columns 1–2) or industry (columns 3–4) following job loss. Displaced stayers are more than 40 p.p. more likely than non-displaced workers to change occupation or industry. Among men, movers are less likely than stayers to switch, implying that relocation helps them find jobs similar to their prior work. Among women, movers and stayers show similar rates of switching, indicating weaker skill continuity and suggesting that female movers often accept lower-quality matches. Men's higher returns to moving thus partly reflect access to better-matched jobs after relocation. Restricting to only full-time workers yields similar results, with a slightly larger gains from moving for full-time women (Table A7).

Table 5: Wage Ratio, Employment, and log Earnings After Job Loss by Moving Status

	Wage Ratio (t/t-1)		Pr(Employed)		ln(Weekly Wages)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Displaced	-0.521***	-0.456***	-0.400***	-0.351***	-0.197***	-0.163***
	(0.018)	(0.014)	(0.010)	(0.008)	(0.016)	(0.012)
Displaced*Moved	0.192**	0.250***	0.157***	0.188***	0.041	0.076*
	(0.077)	(0.051)	(0.050)	(0.028)	(0.067)	(0.042)
Moved	-0.188***	-0.077**	-0.166***	-0.058***	-0.001	-0.007
	(0.053)	(0.032)	(0.029)	(0.014)	(0.033)	(0.022)
Control Mean	1.044	1.058	0.917	0.963	6.028	6.497
Covariates	✓	✓	✓	✓	✓	✓
N	11473	16371	11717	16729	8979	13852

Notes: CPS DWS and March Supplement 1990-2020. In columns 1-2, wage ratio is the ratio between earnings at time t and earnings at time $t-1$. Outcome variable in column 3-4 is a dummy variable equal to 1 if employed at t. In column 5-6, ln(Weekly Wages) is log hourly wages conditional on having positive earnings at time t. Covariates include age, age squared, indicators for race, college, and children; weekly wages, full-time status, public sector indicator, and industry and occupation dummies for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Standard errors are clustered at the matched pair level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Children again shape outcomes (Table A8). Among households without children, men recoup most of their earnings losses when moving, whereas women recover almost none. Among households with children, both men and women experience larger post-move gains, likely because families move only when the expected wage improvement is large enough to offset higher relocation costs. Still, even within these households, men retain a larger advantage.

Taken together, these results show that migration mitigates displacement-induced earnings losses, but unevenly. Married men are both more likely to move and gain more from doing so, while married women are constrained by co-location frictions and caregiving responsibilities, leading to weaker labor market recovery. The evidence suggests that gender inequality after displacement is not solely the result of occupational sorting or labor demand, but also reflects household decision-making that restricts women's ability to relocate in response to shocks.

3.2 Household Level Analysis

The individual-level results reveal pronounced gender differences in mobility after displacement, but migration is ultimately a household decision. To better capture the trade-offs faced by couples, I turn to household-level data. This analysis focuses on married couples observed jointly in the DWS, March Supplement, and ORG. For these couples, both spouses' labor-market outcomes are available for $t-1$ and in the survey year t. Table A1 summarizes variable sources. Restricting to jointly observed couples substantially reduces sample size and likely understates migration rates, since some couples may relocate sequentially rather than together.

3.2.1 Probability of moving by earnings share

A leading explanation for higher household mobility following a husband's job loss is that men are more likely to be the primary earner. If so, households should be more willing to relocate when the displaced worker contributes a larger share of household income. I test this hypothesis by examining how migration varies with the displaced worker's pre-displacement earnings share. The intuition is straightforward: when the job loss affects the main source of income, the household has greater incentive to move to restore lost earnings. Figure A2 shows that men generally contribute a larger share of household earnings, though many women are also primary earners.

I estimate the following regression for married men and married women:

$$\begin{aligned} Moved_{i(t)} = \beta_0 + \beta_1 Displaced_{i(t)} + \beta_2 EarnShare_{it} + \beta_3 Displaced_{i(t)} \times EarnShare_{it} \\ + X'_{i(t)}\Gamma + \theta_s + \theta_t + u_{it} \end{aligned} \tag{3}$$

where *EarnShare* denotes the displaced worker's share of household income in $t-1$. From this specification, I predict post-displacement migration probabilities for male- and female-displaced households across the distribution of earnings shares.

Figure 2 shows a clear gender asymmetry. For male-displaced households, migration rises sharply with the husband's earnings share: when men contribute half of household income, the probability of moving increases by 2.7 percentage points after displacement. In contrast, the migration probability for female-displaced households shows no meaningful relationship with the wife's earnings share: women contributing half of household income are less than 1 p.p. more likely to move. Figure A3 further demonstrates the nonlinear pattern: migration probability increases monotonically with male earnings share but remains flat across the female distribution. Even when husbands earn only 30 percent of total household income, their job loss still raises the likelihood of moving. These patterns suggest that household migration decisions place greater weight on men's earnings, consistent with unequal valuation of spousal income.

Because realized income may reflect prior choices within the household, I construct predicted earnings shares based on spouses' human capital characteristics (Appendix A.3). With predicted earnings share, average migration response is still higher for men relative to women at every level, but the slopes now become similar (Figure A4). Note that the estimates for women are less precise due to limited overlap in predicted distributions.

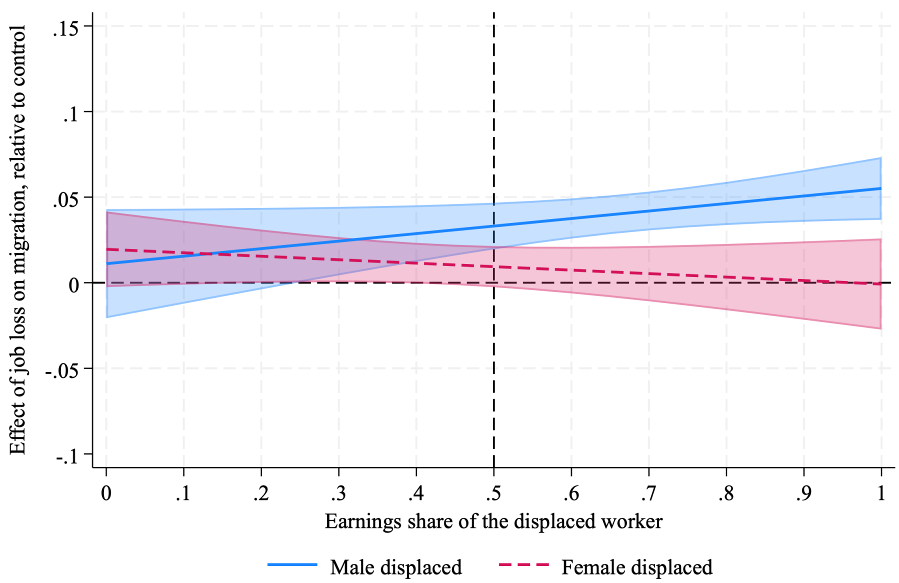


Figure 2: Probability of Moving by Earnings Share in $t-1$

Notes: This figure presents the predicted probability of moving after job loss against the actual earnings share in $t-1$ for male-displaced (blue) and female-displaced (red) households, relative to the control households. Probabilities are predicted after estimating Equation (3).

3.2.2 Earnings and employment

Turning to labor-market outcomes, Table 6 reports employment effects for displaced workers and their spouses. The results parallel the individual-level findings. Displaced workers who do not move experience large employment declines: 36 p.p. for women and 32 p.p (columns 1 and 4). for men. Migration mitigates these losses, particularly for men, who exhibit a mover–stayer employment premium of 24.5 p.p. compared with 14.4 p.p.

for women.

Spouses' employment responses reveal additional asymmetries. The husband of a displaced woman who moves experiences a small employment decline (–1.4 p.p.) relative to the husband of a staying displaced woman. The wife of a displaced man who moves sees a significant 3 p.p. employment decline relative to her counterpart in stayer households, though both numbers are imprecisely estimated. Relocation therefore benefits the displaced worker but tends to reduce the spouse's employment.

Table 6: Own and Spousal Employment Changes by Moving Status

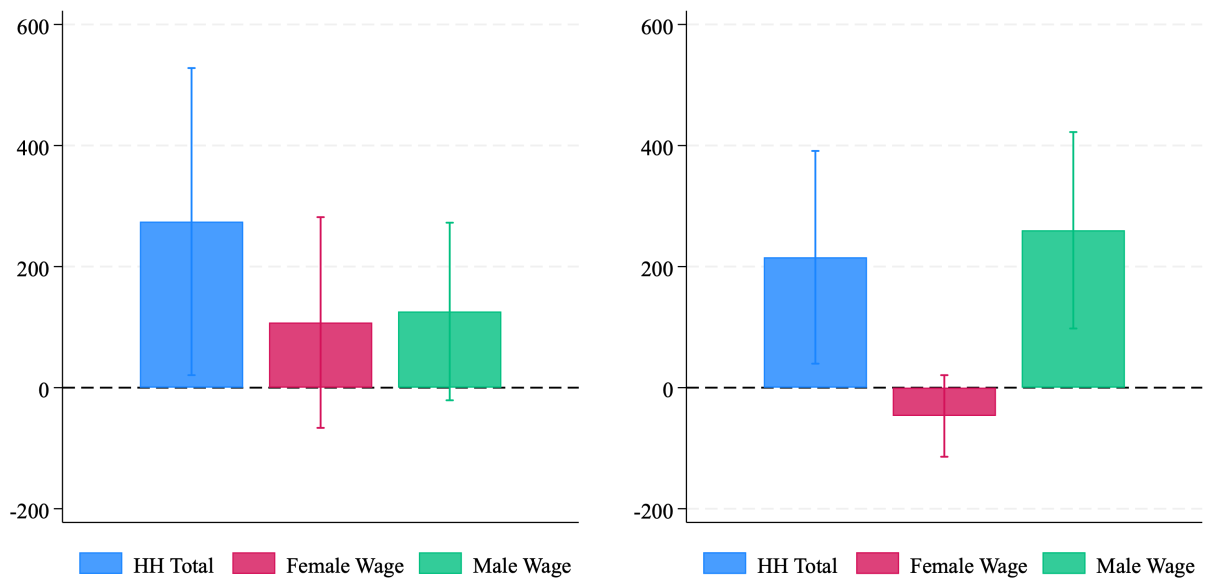
	Female Displaced		Male Displaced	
	(1)	(2)	(3)	(4)
	Female(DW)	Male(Sp)	Female(Sp)	Male(DW)
Displaced	-0.363***	-0.022***	-0.025***	-0.306***
	(0.013)	(0.008)	(0.007)	(0.010)
Displaced*Moved	0.144**	-0.014	-0.031	0.245***
	(0.063)	(0.039)	(0.040)	(0.039)
Moved	-0.159***	-0.030	-0.067***	-0.083***
	(0.034)	(0.021)	(0.025)	(0.021)
Control mean	0.910	0.887	0.717	0.941
Covariates	✓	✓	✓	✓
N	6891	6891	10002	10001

Notes: CPS DWS and March Supplement 1990-2020. DW: the displaced worker him or herself. Sp: spouse of the displaced worker. Covariates include age, age squared, indicators for race, college, and children; weekly wages, full-time status, public sector indicator, and industry and occupation dummies for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, I examine the changes in earnings for displaced workers and their spouses. Three outcome variables are of interest: total household earnings, the earnings of the displaced worker, and the spouse's earnings. Figure 3 plots the estimated moving premium (coefficient α_2 in Equation 2) for each outcome, separately for female-displaced households (Panel a) and male-displaced households (Panel b).

Household total earnings rise significantly for movers relative to stayers in both cases, but the gains are distributed unevenly between spouses. In female-displaced households, both spouses' earnings increase modestly after moving. In male-displaced households, nearly all of the household-level gain comes from the displaced husband, while the wife's earnings decline slightly relative to stayers. Table A9 reports the full estimates.

Overall, the household-level analysis reinforces the central asymmetry documented above. Households are far more responsive to male job loss than to female job loss, even when women are primary earners. Migration improves outcomes for displaced workers but often worsens those of trailing spouses—especially wives. Married women are thus more likely to become "tied movers", experiencing weaker labor-market outcomes following relocation. To isolate the effect of co-location frictions and conduct policy experiments, I next develop a structural model of household job search that incorporates migration, gender-specific job offer processes, and unequal weighting of spousal earnings in household decision-making.



(a) Female-Displaced Households

(b) Male-Displaced Households

Figure 3: Differences between Displaced Movers and Displaced Stayers

Notes: CPS DWS and March Supplement 1990-2020. This figure presents the differential gains from moving for displaced workers relative to non-displaced workers, i.e. coefficients of $Displaced * Moved$ estimated from Equation (2) with 90% confidence interval. The model is estimated with three outcome variables: household total earnings (blue), female earnings (red), and male earnings (green). Left panel shows results for female displaced households, and the right panel for male displaced households.

4 Model

In this section, I introduce a two-location search model for singles and married households. The model formalizes how outside offers and intra-household frictions shape job acceptance decisions, and provides a framework to interpret the empirical patterns documented in Section 3.2. I first present the environment and optimal behavior for singles, then extend the model to married households where decisions are made jointly.

Time is continuous, and the only source of uncertainty is idiosyncratic job loss and job-offer shocks. All agents discount the future at rate r. The economy has two geographic locations, an *inside* and an *outside* location, denoted $l \in \{i, o\}$. Unemployed workers of gender $g \in \{m, f\}$ receive job offers from location l according to a Poisson process with arrival rate α_g^l. There is no on-the-job search. Jobs end exogenously at rate δ_g. Wages are drawn from a gender-specific offer distribution F_g, assumed to be identical across locations. Unemployed workers receive a flow benefit b_g that captures both formal income support (e.g., unemployment insurance) and informal income from home production. Accepting an outside offer requires paying a migration cost ψ per household. Individuals consume all income each period, and there is no saving. Utility function is denoted by $\nu(\cdot)$, which is increasing and can be either linear or concave. Singles and married individuals of the same gender face the same wage offer distribution F_g but may differ in their arrival rates, job-destruction rates, and migration costs.

4.1 Singles

For a non-employed single of gender g, the value function solves:

$$rU_g^{sin} = \nu(b_g^{sin}) + \underbrace{\alpha_g^{i,sin} \int \{\Omega_g^{sin}(w) - U_g^{sin}\}^+ dF_g(w)}_{\text{Inside Offers}} + \underbrace{\alpha_g^{o,sin} \int \{\Omega_g^{sin}(w) - U_g^{sin} - \psi_g^{sin}\}^+ dF_g(w)}_{\text{Outside Offers}}$$

where $\Omega_g^{sin}(w)$ is the value of accepting a job with wage w, and $\{\cdot\}^+ \equiv \max\{\cdot, 0\}$. The migration cost ψ_g^{sin} is a lump-sum disutility in present discounted value terms.

The value of employment at wage w is:

$$r\Omega_g^{sin}(w) = \nu(w) + \delta_g^{sin}[U_g^{sin} - \Omega_g^{sin}(w)]$$

and the next proposition characterizes optimal job-acceptance rules of single workers

Proposition 1 *The value of employment, $\Omega_g^{sin}(w)$, is increasing in w. Consequently, there exist unique reservation wages R_g^i and R_g^o for offers from the inside and outside locations, respectively, that satisfy*

$$\begin{aligned} R_g^i &= \nu(b_g^{sin}) + \frac{\alpha_g^{i,sin}}{r + \delta_g^{sin}} \int_{R_g^i} \nu'(w)[1 - F_g(w)]dw + \frac{\alpha_g^{o,sin}}{r + \delta_g^{sin}} \int_{R_g^o} \nu'(w)[1 - F_g(w)]dw \\ R_g^o &= R_g^i + (r + \delta_g^{sin})\psi_g^{sin} \end{aligned} \tag{4}$$

An unemployed worker accepts an inside (outside) offer if $w \geq R_g^i$ ($w \geq R_g^o$).

Proof. See Appendix B.1 ■

Steady State.—In steady state, inflows to and outflows from unemployment are equal. Let $u_{g,l}^{sin}$ denote the unemployment rate for singles of gender g in location l. The flow balance condition is

$$\underbrace{u_{g,l}^{sin} \times \{\alpha_g^{i,sin}[1 - F(R_g^i)] + \alpha_g^{o,sin}[1 - F(R_g^o)]\}}_{\text{Outflow from Unemployment}} = \underbrace{\delta_g^{sin} \times (1 - u_{g,l}^{sin})}_{\text{Inflow to Unemployment}}$$

Because locations are symmetric, $u_{g,i}^{sin} = u_{g,o}^{sin} \equiv u_g^{sin}$. Rearranging the equation, we have

$$u_g^{sin} = \frac{\delta_g^{sin}}{\alpha_g^{i,sin}[1 - F(R_g^i)] + \alpha_g^{o,sin}[1 - F(R_g^o)] + \delta_g^{sin}} \tag{5}$$

Similarly, for those who are employed at wage $w' < w$, outflows equal inflows into this group. The flow-balance condition for employed workers is given by:

$$u_g^{sin} \times \{\alpha_g^{i,sin}[F_g(w) - F(R_g^i)] + \alpha_g^{o,sin}[F_g(w) - F(R_g^o)]\} = (1 - u_g^{sin}) \times \delta_g^{sin} \times H^g(w)$$

where the left hand side represents flow from unemployment to jobs with wage less than w, and the right hand side show outflows from those wages into unemployment. $H_g(w)$ denotes the steady-state wage distribution. While $F_g(w)$ is exogenous, $H_g(w)$ is an endogenous object that depends on worker's job acceptance strategy.

Plugging in u_g^{sin} from Equation (5), we can derive the steady-state cumulative distribution of employed singles:

$$H_g(w) = \frac{\alpha_g^{i,sin}[F_g(w) - F(R_g^i)] + \alpha_g^{o,sin}[F_g(w) - F(R_g^o)]}{\alpha_g^{i,sin}[1 - F(R_g^i)] + \alpha_g^{o,sin}[1 - F(R_g^o)]} \tag{6}$$

Higher reservation wages shift the distribution of accepted wages up in a First Order Stochastic Dominance (FOSD) sense.

4.2 Married Households

The household model extends the joint search framework of Guler et al. (2012) to include migration costs, gender heterogeneity in labor-market parameters, and intra-household decision weights. There are four possible household states depending on the spouses' employment status: (1) both unemployed (dual-unemployed); (2) husband employed, wife unemployed (male-headed worker-searcher); (3) wife employed, husband unemployed (female-headed worker-searcher); and (4) both employed (dual-employed). Couples cannot live apart, and there is no marriage formation or divorce decision. This restriction facilitates empirical implementation, as the data do not record the labor market status of spouses living in separate locations.

4.2.1 Household Flow Utility

Let the wife's Pareto weight be $\beta \in [0,1]$, and the husband's weight is $1-\beta$. The usual practice in household search literature is to use the unitary household framework with full income pooling. The household maximizes

$$\max_{c_m, c_f} \quad (1-\beta)\nu(c_m) + \beta\nu(c_f)$$
$$s.t. \quad c_m + c_f = I_m + I_f$$

where I_g is spouse g's income, with $I_g = w$ if employed and $I_g = b_g$ if unemployed. The optimal consumption bundle consists of fixed shares of total household income

$$c_m^* = \lambda(\beta)(I_m + I_f), c_f^* = (1-\lambda(\beta))(I_m + I_f),$$

where the share λ is a function of β. In Appendix B.3, I derive the expressions with CRRA utility function. This special case has two implications: First, β affects reservation wages, and thus labor market transitions, only by rescaling the migration cost ψ. Second, while β changes the consumption division within the household, it has a symmetric effect on the labor market transitions of men and women. For example, $\beta = 0.1$ and $\beta = 0.9$ imply different consumption bundles but yield the same set of reservation wages. The household first maximizes total income and then allocates it according to the Pareto weight.

However, this prediction conflicts with the empirical evidence in Section 3.2, where household migration responses differ by the gender of the displaced spouse even when earnings shares are similar. To capture this asymmetry, I move to the case without income pooling in which each worker's utility is a function of their own income:[9]

[9] In collective household models, the sources of income matter for household resource allocation. When one spouse's income increases, there is both an income effect that increases both members' consumption but also an empowerment effect that increases the share of resources that spouse is assigned. See for example Chiappori (1992); Browning and Chiappori (1998).

$$W(I_m, I_f; \beta) = (1-\beta)\nu(I_m) + \beta\nu(I_f) \tag{7}$$

Though not directly sharing income, members of the household care about joint utility/value when making labor market transition decisions, thus an increase in spousal income will still affect their own search behaviors through this channel. β measures the household's relative weight on the wife's utility, which can be interpreted as the degree to which her career or well-being influences joint decisions. For example, $\beta < 0.5$ can represent social norms that prioritize the husband's employment.

4.2.2 Value Functions

Dual-Searcher Households. The value function of a household where both spouses are unemployed is:

$$rU = W(b_m, b_f; \beta) + \underbrace{\sum_{g\in\{m,f\}} \alpha_g^i \int \{\Omega_g(w) - U\}^+ dF_g(w)}_{\text{Offers from inside location}} + \underbrace{\sum_{g\in\{m,f\}} \alpha_g^o \int \{\Omega_g(w) - U - \psi_h\}^+ dF_g(w)}_{\text{Offers from outside location}}$$

where $\Omega_g(w)$ is the value when spouse g is employed at wage w while the other remains unemployed. If either spouse accepts an outside offer, the household pays a migration cost ψ_h and transitions to a worker-searcher state headed by the accepting spouse. Because the model is in continuous time, the probability of receiving an inside and an outside offer at the same time, as well as the probability of both spouses receiving offers at the same time are equal to zero. Therefore, households only make one decision at a time.

Worker-Searcher Households. Consider a male-headed household where the husband is employed at wage w and the wife searches. The value function is:

$$\begin{aligned} r\Omega_m(w) = \; & \underbrace{W(w_m, b_f; \beta)}_{\text{Household flow value}} + \underbrace{\delta_m[U - \Omega_m(w)]}_{\text{Exogenous separation}} \\ & + \alpha_f^i \int \{\underbrace{T(w, w_f) - \Omega_m(w)}_{\text{Enter dual-employment}}, \underbrace{\Omega_f(w_f) - \Omega_m(w)}_{\text{Breadwinner cycle}}\}^+ dF_f(w_f) \\ & + \alpha_f^o \int \underbrace{\{\Omega_f(w_f) - \Omega_m(w) - \psi_h\}}_{\text{Breadwinner cycle}}^+ dF_f(w_f) \end{aligned}$$

On the right hand side, the first and second terms in the first line capture the flow value part and exogenous job separation. The second line describes the value for inside offers. When the wife receives an inside job offer, the household faces three possibilities: First, she accepts the offer and the husband remains employed, in which case they transition into dual-employment status. Second, she accepts the offer and the husband voluntarily quits to re-enter search, in which case they transition to a female-headed household. Third, if the offer is too low, she turns down this offer and continues searching. The second case is the "breadwinner cycle" (Guler et al., 2012), where spouses alternate as the sole earner of the household to facilitate job switching. This typically occurs when the husband was employed at a relatively low wage, when the option value of searching for jobs is still high. Therefore, this option is also viewed as a costly form of on-the-job search, allowing couples to climb up the job ladder absent on-the-job search.

When the wife receives an outside offer and the couple decides that she should take it, the husband must quit his current job. After paying the migration cost, the entire household moves to the new location as a female-headed household. This is another form of the "breadwinner cycle", which creates tied movers, and captures the co-location frictions households face.

A symmetric expression defines the value for a female-headed household where the wife is employed and the husband searches.

Dual-Worker Household. When both spouses are employed at wages (w_m, w_f),

$$rT(w_m, w_f) = W(w_m, w_f; \beta) + \delta_m[\max\{\Omega_f(w_f), U\} - T(w_m, w_f)] + \delta_f[\max\{\Omega_m(w_m), U\} - T(w_m, w_f)]$$

Job loss by either spouse leads the household to decide whether to remain with one earner or return to joint unemployment. These decisions depend on the respective value functions and the strategic value of job switching.

4.2.3 Reservation Wages of Married Households

Household decisions can be summarized by reservation wages that make the household indifferent between remaining in the current state and accepting an offer. For dual-unemployed households, the reservation wages R_g^{1i} and R_g^{1o} for inside and outside offers are defined by:

$$\Omega_f(R_f^{1i}) = U = \Omega_m(R_m^{1i})$$
$$\Omega_f(R_f^{1o}) = U + \psi_h = \Omega_m(R_m^{1o})$$

These expressions imply that a household accepts an offer only if the gain from employment exceeds the value of remaining unemployed (plus the migration cost, if applicable).

In a worker-searcher household, let $R_g^{2T}(w)$ denote the inside wage offer that would induce the searching spouse g to accept the offer and transition the household to a dual-employed state, holding the working spouse's wage fixed at w. The thresholds satisfy:

$$T(w_m, R_f^{2T}(w_m)) = \Omega_m(w_m), \quad T(R_m^{2T}(w_f), w_f) = \Omega_f(w_f)$$

Let $R_g^{3i}(w)$ ($R_g^{3o}(w)$) denote the reservation wages at which the household would engage in inside (outside) breadwinner cycle. These thresholds satisfy:

$$\Omega_m(R_m^{3i}(w_f)) = \Omega_f(w_f), \quad \Omega_f(R_f^{3i}(w_m)) = \Omega_m(w_m)$$
$$\Omega_m(R_{3o}^{m}(w_f)) = \Omega_f(w_f) + \psi_h, \quad \Omega_f(R_f^{3o}(w_m)) = \Omega_m(w_m) + \psi_h$$

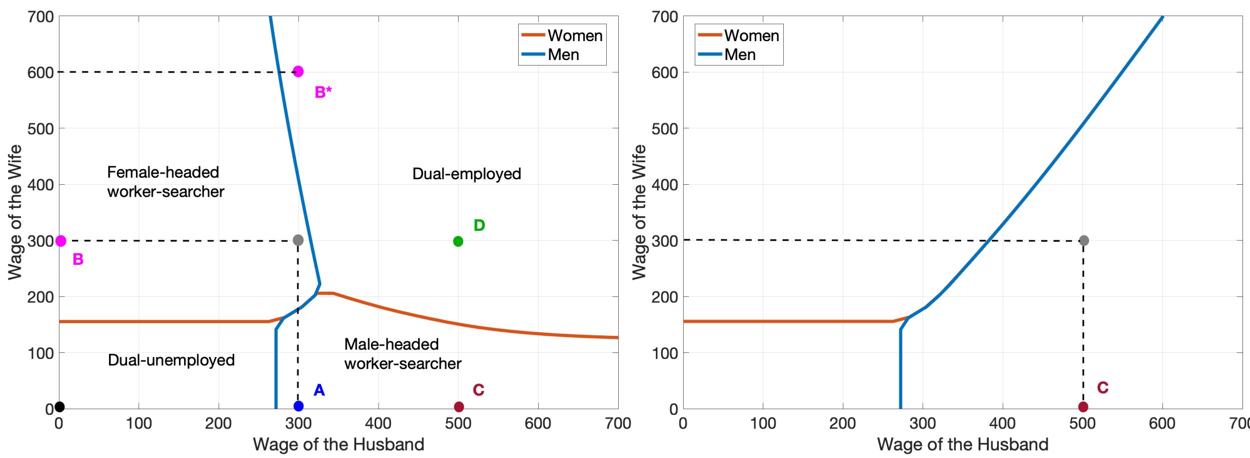
Let $\phi_g(w) = min\{R_g^{2T}(w), R_g^{3i}(w)\}$ denote the searching spouse's effective reservation wage for an inside offer, conditional on the working spouse's wage w. This function captures the wage at which the searching spouse will move out of unemployment, and the spouses will either transition to dual employment or switch roles via the breadwinner cycle. This cutoff depends on the working spouse's wage, illustrating how spousal wages shape each other's job-acceptance decisions.

Figure 4 presents the reservation wages for inside (Panel a) and outside offers (Panel b) for both spouses, with the horizontal axis representing wages of the husband and the vertical axis representing the wages of the wife. For inside offers, these reservation wages divide the (w_m, w_f) plain into four regions: dual unemployment, male-headed and female-headed worker–searcher states, and dual employment. For outside offers, dual-employed status does not exist as moving for one spouse's job requires the other to quit.

When both spouses are unemployed, reservation wages ($R_g^l, g \in \{m, f\}, l \in \{i, o\}$) are constant. As one spouse becomes employed at a low wage, the other's reservation wages increase with that wage for both inside and outside offers—generating breadwinner cycles where spouses alternate as the household's sole earner while climbing the job ladder. We can use Figure 4a to illustrate the inter-dependent job transitions between spouses. Consider a household in which the husband is currently employed at wage \$300 and the wife is searching for jobs (Point A). If the wife's new offer is \$600, the wage pair (\$300,\$600) at point B^* exceeds both spouses' reservation wages. They will directly become a dual-employed household.

If the wife receives an inside offer of \$300, she will take it as it exceeds her reservation wages, as indicated by the red line. Conditional on the wife's new wage offer, the man's wage of \$300 now falls under his reservation wages, thus he will quit into unemployment and search for jobs again (Point B). If he then receives an outside offer of \$500, he will accept this offer, the wife quits her current \$300 job, and the family move to the new location (Point C). As there is no location heterogeneity, the new location now becomes their inside location and the wife starts to search for jobs at point C. If she now gets an inside offer of \$300, she will accept it, and the household becomes a dual-employed household with wage pair (\$500,\$300) at point D. The inside and outside breadwinner cycles thus help the household achieve higher value by temporarily giving up low spousal incomes.

The full system of law-of-motion equations and the derivation of steady-state distributions are provided in Appendix B.2.



(a) Inside Reservation Wages (b) Outside Reservation Wages

Figure 4: Reservation Wages for Inside and Outside Offers

Notes: This figure shows the reservation wages for inside (Panel a) and outside offers (Panel b). The x-axis is the wage of the husband, and the y-axis is the wage of the wife. Red (blue) line represents reservation wages of the wife (husband). The utility function is linear $v(w) = w$.

4.3 The Role of Migration

Access to outside offers is a double-edged sword: on the one hand, it opens up opportunities for workers and accelerates re-employment after job loss. At the aggregate level, it can also reallocate workers out of distressed areas and facilitate economic recovery. However, from a household perspective, trailing spouses are forced to quit their current job and bear large labor market losses. Interacted with unequal weighting and gender difference in labor market opportunities, migration will affect equilibrium gender inequality.

Proposition 5 in Guler et al. (2012) establishes that migration makes the optimal search strategies of household members interdependent even under risk neutrality. While their model allows couples to reside in different locations subject to a flow-utility cost, I instead assume that both spouses must live together—specifically, a worker must quit their job when their spouse accepts an outside offer. I also extend their framework by introducing unequal weighting of spousal income and gender heterogeneity in all labor market parameters. In Appendix B.4, I show that under these assumptions, the main insights from Guler et al. (2012) remain: removing outside offers collapses the household problem into two independent single-agent search problems.

The intuition is as follows: In a standard single-agent search model, a higher flow value of unemployment—such as from more generous unemployment insurance—raises the reservation wage because accepting a job entails giving up a more valuable outside option. Consider a male-headed household in which the husband is employed at a wage just above his dual-unemployed reservation wages. If the wife accepts a new job, her income raises the household's flow utility. When only inside offers exist, this increase persists regardless of the husband's job choice, leaving his search behavior unchanged and preventing any breadwinner cycle. With outside offers, however, household utility from the wife's income works similarly as unemployment insurance for the husband, since accepting an outside offer requires her to quit, so this "insurance" disappears. Anticipating this loss, the husband becomes more selective over both inside and outside offers, increasing his reservation wages. A female job acceptance can thus trigger an inside breadwinner cycle. Conversely, if the wife's new job pays sufficiently well (Point D), the husband recognizes that finding an outside offer high enough to justify relocation is unlikely. He becomes a tied stayer, lowering his inside reservation wage, and her job acceptance no longer induces a breadwinner cycle.

5 Estimation

5.1 Parameterization

I estimate the model using the *Method of Moments*. The estimator minimizes the distance between a set of empirical moments and their theoretical counterparts, which are calculated by solving the model's steady-state conditions. Standard errors are calculated using the classic "sandwich" formula.[10]

[10]The asymptotic variance is computed as $Var(\hat{\Theta}) = (G'WG)^{-1}G\hat{S}G(G'WG)^{-1}$, where G is the Jacobian matrix—partial derivative of moment conditions with respect to each parameter evaluated at the estimates; $\hat{S}$ is the bootstrapped covariance matrix of the empirical moments; and weighting matrix W is the inverse

The model is set to a weekly frequency, with a discount rate of $r = 0.002$, corresponding to an annual rate of 10 percent. The utility function is linear, so household flow utility simplifies to

$$W(I_m, I_f; \beta) = (1 - \beta)I_m + \beta I_f$$

where $\beta \in [0,1]$ is the intra-household weight on the wife's income.

Wages are drawn from gender-specific log-normal offer distributions with parameters μ_g and σ_g, which are the same for married and unmarried workers of gender g. This assumption enables a distinction between gender-based and marriage-based wage effects.

Parameters for singles are estimated separately for men and women:

$$\Theta_g^{Sin} = \{ \underbrace{\mu_g, \sigma_g}_{\text{Offer Distribution}}, \underbrace{\alpha_g^{i,sin}, \alpha_g^{o,sin}}_{\text{Offer Arrival}}, \underbrace{\delta_g^{sin}}_{\text{Job Destruction}}, \underbrace{\psi_g^{sin}}_{\text{Migration Cost}}, \underbrace{b_g^{sin}}_{\text{Unemployment Benefits}} \}$$

I then take the estimated wage offer distributions $(\hat{\mu}_g, \hat{\sigma}_g)$ from singles as given and jointly estimate the remaining household-level parameters:

$$\Theta^{HH} = \{ \underbrace{\alpha_m^i, \alpha_m^o, \alpha_f^i, \alpha_f^o}_{\text{Offer Arrival Rates}}, \underbrace{\delta_m, \delta_f}_{\text{Job Destruction}}, \underbrace{\psi_h}_{\text{Mig. Cost}}, \underbrace{b_m, b_f}_{\text{Unemployment Benefits}} \underbrace{\beta}_{\text{Wife's Weight}} \}$$

Married individuals are allowed to exhibit different search behaviors from singles, and migration cost is at the household level. The household additionally chooses job transitions based on the weight placed on the wife's income, captured by β.

5.2 Identification

Singles. Identification of labor market parameters for singles follows standard results from continuous-time search models. Under the recoverability condition and assuming a log-normal wage offer distribution with parameters (μ, σ), the offer distribution can be recovered from the observed wage distribution (Flinn and Heckman, 1982). In particular, the lowest observed wage serves as an extreme value estimator of the reservation wage and converges to the true lower bound at rate N.[11] Empirical reservation wages are defined as

$$\hat{R}_g^{1i} = \min_i w_g^i \text{ for stayers}, \quad \hat{R}_g^{1o} = \min_i w_g^o \text{ for migrants}$$

The job destruction rate, δ_g, is identified from the average job tenure, $1/\delta_g$. The av-

of the diagonal of $\hat{S}$, adjusted to reflect importance of different moments.

[11] In practice, I trim wages at the bottom 2 percent by gender to mitigate the influence of outliers.

erage unemployment duration corresponds to the inverse of the total job-finding rate, which combines both local and outside offers:

$$\text{E(Unemployment Duration)}_g = \frac{1}{\alpha_g^i * [1 - F_g(R_g^{1i})] + \alpha_g^o * [1 - F_g(R_g^{1o})]} \tag{8}$$

The share of unemployment-to-employment (UE) transitions involving a move is

$$\text{MigrationShare}_g = \frac{\alpha_g^o * [1 - F_g(R_g^{1o})}{\alpha_g^i * [1 - F_g(R_g^{1i})] + \alpha_g^o * [1 - F_g(R_g^{1o})]} \tag{9}$$

Conditional on observed reservation wages, the unemployment duration (Equation 8), migration share (Equation 9), and steady-state wage distribution (Equation 6) depend only on the offer arrival rates and the offer distribution parameters. Therefore, these moments jointly identify $(\alpha^i, \alpha^o, \mu, \sigma)$.

To remove excessive wage dispersion driven by observable characteristics, I first estimate a Mincer regression of log weekly wages on age-group indicators, college attainment, race, full-time status, and industry, occupation, state, and year fixed effects, separately by gender. Residualized wages are then constructed as the sum of individual residuals and the mean predicted wage for gender g. I use the mean and selected percentiles (10th, 25th, 75th, and 90th) of the residualized wage distribution as targeted moments for estimation.

Finally, unemployment benefits b and migration costs ψ are backed out from the inside and outside reservation wage equations (Equations 4). The difference between inside and outside reservation wages identifies ψ: when moving is costly, workers require a higher outside offer to accept relocation.

Married. Similar identification arguments apply to married couples. Since wage-offer parameters are imported from the singles' problem, the average mover-stayer wage gap of married workers identify their flow values of unemployment and migration cost. The intra-household weight β is identified from gender differences in migration rate and earnings gains following a move. Conditional on other labor market parameters (e.g. offer distribution, offer arrival rates), a larger migration gap between men and women, or disproportionately larger gains from moving for female workers, imply a lower β. In these cases, greater returns are required for women to trigger relocation.

When computing model-implied moments, I aggregate over household types using their steady-state shares (Equations 11–14), thereby translating household-level behavior into gender-level statistics for estimation.

5.3 Results

5.3.1 Singles' Parameters

Table 7 compares model-implied moments with their empirical counterparts for single men and single women. For the average unemployment duration, the migration share, and the average employment duration, moments are well matched. For the wage distribution, the model also does a good job in matching the key percentiles.

Table 7: Model-Implied and Empirical Moments

	Single Men		Single Women	
	(1)	(2)	(3)	(4)
Moments	Model	Data	Model	Data
M1. Average unemployment duration	15.92	15.92	15.21	15.21
M2. Migration share	0.21	0.21	0.16	0.16
M3. Average employment duration	205	205	216	216
M4. Mean wages	577	589	432	438
M5. 10th percentile	281	281	213	217
M6. 25th percentile	370	371	282	282
M7. 75th percentile	708	691	531	514
M8. 90th percentile	951	959	706	718

Notes: This table presents the moments targeted in estimation of single's parameters for men (column 1-2) and women (column 3-4). Column 1 and 3 present model-implied moment values using the estimates, and column 2 and 4 report the corresponding moment value calculated from data.

Table 8 presents the estimated parameters. For single men (Panel A), the weekly inside offer arrival rate is 0.050, or roughly 0.20 on a monthly basis. Outside offers arrive less frequently, at 0.013 per week. For single women (Panel B), the corresponding rates are 0.055 and 0.011. Women thus receive local offers slightly more frequently but have fewer external opportunities, consistent with lower geographic mobility.

Turning to the wage offer distribution, the implied mean weekly wage offers are \$571.6 for men and \$434.5 for women. This 31.6% gap likely reflects labor demand factors such as discrimination and differences in firm-specific pay premiums. Men also face a wider offer distribution ($\sigma_m > \sigma_f$), implying a higher potential returns from moving for them.

The flow value of unemployment b and migration cost ψ are backed out from the reservation wage equations. The estimates imply negative values of b for both genders (–3,475 for single men and –3,069 for women), reflecting short unemployment durations and low reservation wages observed in the data. Negative flow values are not uncommon in search model estimations. Hornstein et al. (2011) find that under reasonable model parameterization, a negative b is needed to generate observed wage dispersion. [12]

Table 8: Estimated Parameters - Single

Parameters	(1) Estimates	(2) s.e.	(3) Sensitivity
Panel A: Single Men			
Inside offer arrival rates, α_m^i	0.050	0.001	M1,M2,M5
Outside offer arrival rates, α_m^o	0.013	0.0003	M2,M1,M8
Job destruction rate, δ_m	0.005	0.0001	M3,M1,M2
Location parameter, μ_m	6.23	0.008	M6,M5,M7
Shape parameter, σ_m	0.489	0.007	M8,M6,M5
Unemployment value, b_m	-3475	80.6	
Migration cost, ψ_m	161	1.48	
Panel B: Single Women			
Inside offer arrival rates, α_f^i	0.055	0.001	M1,M2,M5
Outside offer arrival rates, α_f^o	0.011	0.0003	M2,M1,M8
Job destruction rate, δ_f	0.005	0.0001	M3,M1,M2
Location parameter, μ_f	5.96	0.008	M6,M5,M7
Shape parameter, σ_f	0.470	0.008	M8,M5,M6
Unemployment value, b_f	-3069	70.9	
Migration cost, ψ_f	826	7.62	

Notes: This table presents estimation results for single workers, with Panel A for single men and Panel B for single women. Column (1) presents the point estimates obtained from the Method of Moments. Column (2) reports bootstrapped standard errors. Column (3) presents the top 3 most sensitive moments of the corresponding parameter based on the method proposed by Andrews et al. (2017).

Migration cost is substantially higher for women (826) than for men (161). When expressed relative to average weekly wages, this corresponds to roughly two weeks of pay for women but only 0.3 weeks for men, highlighting potential gender asymmetries in geographic mobility constraints. For example, women may be more attached to their extended family than men, which is reflected as a higher migration cost as well as a tendency to specialize their job search in the local labor market.

Column (3) of Table 8 reports the three most influential moments for each parameter,

[12] b captures both financial and psychological costs of joblessness. If workers are willing to take a low wage job quickly given the large observed wage dispersion, they must "hate" unemployment so much that they would be willing to pay to get out of it, leading to a negative value of b.

based on the sensitivity metric of Andrews et al. (2017).[13] These results confirm the identification arguments outlined earlier. For instance, the inside and outside offer arrival rates are most sensitive to unemployment duration and migration share, aligning with theoretical expectations.

Additional tests for model fit. Figure A6 illustrates that the model closely replicates the observed steady-state wage distribution for both men and women, matching the central mass of the distribution particularly well. Figure A7 provides a visual assessment of model fit. It compares model-implied moments with the range of their empirical counterparts calculated from a bootstrapped sample, for single men (left panel) and women (right panel). The model fits the data well, with all predicted moments falling within the corresponding intervals.

5.3.2 Married Couples' Parameters

Using the wage offer parameters from singles, I jointly estimate the remaining ten household parameters by matching model-implied moments to empirical counterparts listed in Table 9. Higher weights are assigned to average unemployment duration, migration share, and average employment duration. As a result, these moments are well matched to their empirical ones. Wages are assigned a lower weight in estimation. Mean accepted wages for stayers are well matched, while the model overestimates the mean wages for movers and the mover-stayer wage gap at the 10th percentile.

Table 9: Model-Generated Moments and Data Targets - Married

	Married Men		Married Women	
	(1)	(2)	(3)	(4)
Moments	Model	Data	Model	Data
M1,M2. Average unemployment duration	14.70	14.71	17.85	17.86
M3,M4. Migration share	0.158	0.157	0.094	0.095
M5,M6. Average employment duration	304	304	267	267
M7,M8. Mean accepted wages, stayer	620	650	437	427
M9,M10. Mean accepted wages, movers	726	697	590	464
M11,M12. Mover-stayer wage gap 10 pct.	92.5	30.1	88.3	12.3

Notes: This table presents model-implied and empirical values of the moments for married workers. Column 1-2 report the values for married men and column 3-4 for married women.

[13] The sensitivity of each parameter to the moments is calculated as $Sensitivity = [G'WG]^{-1}GW$, where G is the Jacobian and W is the weighting matrix. Since the moments have different scales, I multiply the columns of the sensitivity matrix by the standard deviation of the corresponding empirical moment.

The estimated parameters are reported in Table 10. Panel A presents estimates for married men, Panel B for married women, and Panel C for household-level parameters. Because the offer distribution parameters (μ_g, σ_g) are taken from the single's estimates, their sampling error may introduce downward bias in the second-step variance estimates (Murphy and Topel, 1985). To address this, I apply the correction procedure proposed in Murphy and Topel (1985) to account for the estimation error carried over from the first step. The standard errors reported in the table reflect this correction.

Table 10: Estimated Parameters - Married

	(1)	(2)	(3)
Parameters	Estimates	s.e.	Sensitivity
Panel A: Married Men			
Inside offer arrival rates, α_m^i	0.078	0.0029	M7,M1,M8
Outside offer arrival rates, α_m^o	0.029	0.0021	M9,M12,M10
Job destruction rate, δ_m	0.0033	0.00003	M5,M12,M8
Value of unemployment, b_m	-4340.8	131.4	M1,M10,M12
Panel B: Married Women			
Inside offer arrival rates, α_f^i	0.050	0.0015	M2,M10,M12
Outside offer arrival rates, α_f^o	0.024	0.0018	M9,M12,M7
Job destruction rate, δ_f	0.0037	0.00004	M6,M8,M12
Value of unemployment, b_f	-2214.6	235.6	M7,M8,M12
Panel C: Household Level			
Migration cost, ψ	7.418	1630.1	M10,M11,M12
Female weight, β	0.386	0.0343	M8,M12,M10

Notes: Column (1) presents the point estimates obtained from the Method of Moments. Column (2) reports bootstrapped standard errors. Column (3) presents the top 3 most sensitive moments of the corresponding parameter based on the method proposed by Andrews et al. (2017).

Several patterns emerge. First, offer arrival rates are higher for married men (inside 0.078, outside 0.029) than for married women (inside 0.050, outside 0.024), pointing to within-household specialization in job search. This finding aligns with Faberman et al. (2025), who show that men are more effective than women in finding jobs from unemployment. Married men also have higher arrival rates than single men. Second, married workers face lower job destruction rates than single workers. This may reflect a preference for less risky employment among married individuals or selection of workers with more stable jobs into marriages.

Third, the flow value of unemployment remains negative for married individuals, as in the singles' case. However, married men have a significantly lower b than single men whereas married women have a higher b than single women. These differences capture household specialization, with married women more likely to specialize in home production. The estimated migration cost $\psi = 7.4$ is substantially lower than the corresponding values for single men (161) and women (826). While counterintuitive at first glance, this result is consistent with the model assumptions. Household migration entails two different costs: the direct migration cost ψ, and the forgone earnings of the trailing spouse. The small point estimate for ψ suggests that the majority of the cost is already captured through lost spousal income.

The intra-household weight on female income is $\hat{\beta} = 0.386$. This implies that women's earnings are valued at approximately 63% of men's in household decision-making ($\beta/(1-\beta) \approx 0.629$). This aligns with Section 3.2, where the wife's earnings share had little effect on migration. Using a different model, Jayachandran et al. (2024) estimated that the relative weight on woman's income compared to man's income is 0.481 for Germany and 0.795 for Sweden. However, these numbers may not be directly comparable as they come from different model specifications. In addition, cultural norms and labor market institutions vary, and displaced workers may face different household bargaining dynamics than those making job-to-job transitions.

Similarly, column (3) of Table 10 reports the three most influential moments for each parameter. As discussed above, the flow value of unemployment, migration cost, and the female income weight are primarily identified from wage-related moments.

5.4 Model Validation

A natural question is whether the estimated model can reproduce the empirical patterns documented in Section 3. Using the parameter estimates from Section 5, I simulate panel data on job transitions for married workers and replicate the key empirical exercises: the probability of moving after job loss and the evolution of earnings for displaced workers and their spouses. Overall, the simulated outcomes align with the empirical evidence, suggesting that the model captures the main behavioral responses to displacement and migration.

Several caveats qualify the mapping between the empirical and simulated results. First, in the DWS, the exact timing of job loss is not observed, except that those jobs were lost sometime in the previous year.[14] As a result, the empirical migration responses in Table 2 reflect a weighted average over different durations since displacement. If the

[14]The empirical analysis only uses those that lost their jobs in the previous year.

sample disproportionately includes workers who lost their jobs closer to the survey date, the observed migration rate will appear lower than if the survey captured a uniform distribution over the post-displacement period. Second, the model includes migration only for job-related reasons (and trailing-spouse effects), whereas in the data, some individuals move for non-job reasons such as family care or housing. These factors introduce discrepancies in levels but not in the qualitative patterns the model seeks to explain.

5.4.1 Probability of moving after job loss

I assume that displaced workers are surveyed uniformly between one and 52 weeks after job loss. Columns (1) and (3) of Table 11 present the simulated probabilities of moving for displaced and non-displaced workers by gender, while columns (2) and (4) show the corresponding empirical values.

Table 11: Moving Rate Within 1 Year (Uniform Survey Week)

	Married Men		Married Women	
	(1)	(2)	(3)	(4)
	Model	Data	Model	Data
Displaced (D)	0.120	0.095	0.057	0.054
Non-displaced (ND)	0.031	0.043	0.034	0.035
Difference (D-ND)	0.089	0.052	0.023	0.019

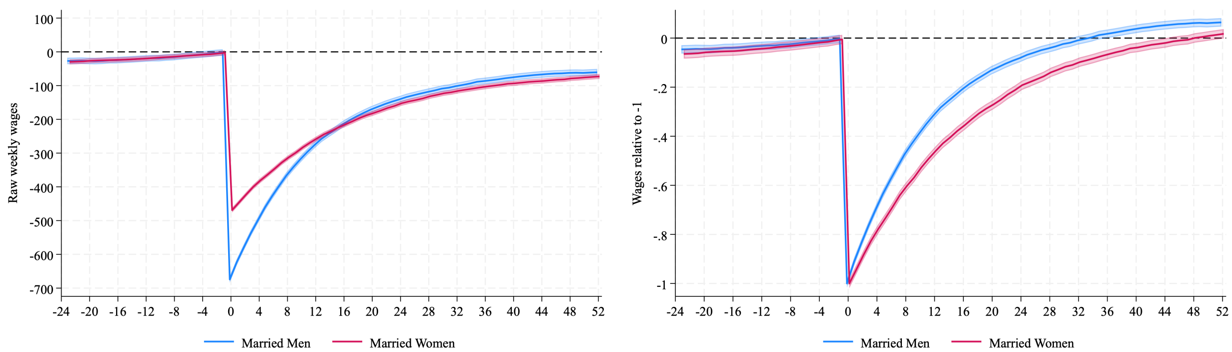
Notes: The table compares simulated and empirical probabilities of moving for displaced and non-displaced married workers. In the simulated data, I assume uniform timing of displacement within the previous year and compute the weighted average of migration probabilities.

For women, the model replicates both the level and the displacement-induced increase in migration almost exactly. For men, the simulated displacement response is somewhat larger than observed in the data: the model predicts a migration probability of 12.0% for displaced married men versus 9.5% in the data. This overprediction could reflect the timing issue noted above: men are overrepresented among recently displaced workers in the sample. Despite this, the model successfully reproduces the key qualitative finding that households respond more strongly to male than to female job loss.

5.4.2 The cost of job loss

The model also reproduces the asymmetric earnings trajectories following displacement. The DWS only provides two wage observations per individual (before and after displacement), the simulated panel allows tracking weekly earnings over time. Figure 5 plots these trajectories for married men (blue) and married women (pink), from 24 weeks before to 52 weeks after job loss. Panel (a) shows raw weekly earnings (including zeros during unemployment), while panel (b) normalizes earnings to pre-displacement levels at $t = -1$.

Consistent with columns 1-2 of Table 4, men experience larger initial income losses because of higher baseline earnings (Figure 5a) but also faster recoveries (Figure 5b).[15]



(a) Raw Weekly Earnings

(b) Wage Ratio Relative to $t = -1$

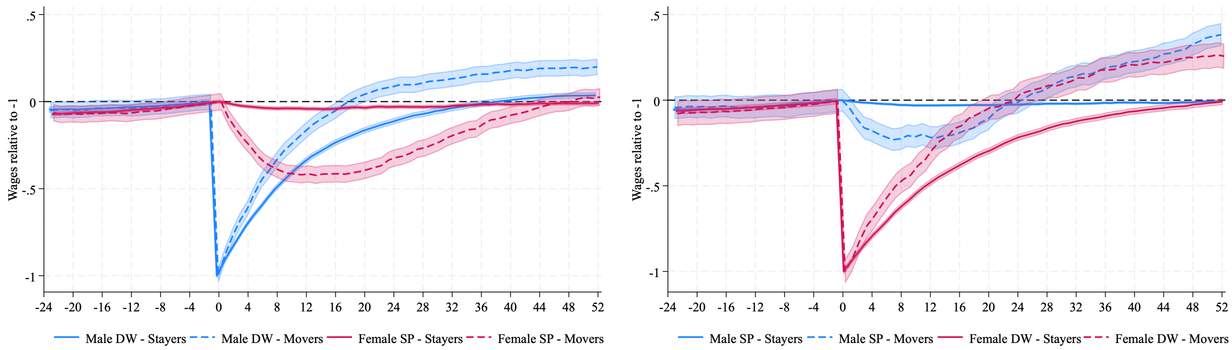
Figure 5: Cost of Job Loss for Married Workers

Notes: This figure presents model-simulated earnings trajectories for workers who experience exogenous separation. Left panel presents the raw earnings trajectories, which include zero earnings while still unemployed, and the right panel presents changes in wage ratio, as defined by earnings in each period divided by earnings in time $t = -1$.

Figure 6 extends the analysis by separating households that moved after job loss from those that stayed. Several insights emerge. First, displaced workers who move recover earnings substantially faster than stayers, mirroring the empirical estimates in Table 4. Second, spouses of displaced workers incur clear costs as trailing spouses. For female trailing spouses, earnings losses are persistent driven by lower arrival rates; for male trailing spouses, the losses are short-lived, and earnings recover within a year. This asymmetry closely mirrors the empirical evidence from Figure 3, where male spouses' labor-market reentry is much faster than that of female spouses.

Exact magnitudes cannot be compared directly because of the same right-censoring problem, i.e. survey respondents are observed for differing intervals following job loss, but the qualitative consistency is striking. The model reproduces both the asymmetric migration response to male and female displacement and the unequal post-move recovery between leading and trailing spouses, two of the core empirical facts motivating the analysis.

[15] Because the model features no on-the-job search and identical offer distributions before and after displacement, recoveries are fast, and earnings return to pre-displacement levels within about one year.



(a) Male-displaced

(b) Female-displaced

Figure 6: Earnings Trajectories for Displaced Workers and Their Spouses
Notes: The left panel presents simulated wage ratio trajectories for the displaced male worker and the female spouse, and the right panel shows that for the displaced female workers and the male spouse. Wage ratio is calculated as wages in each period divided by wages at $t = -1$. Displacement events happen at $t = 0$.

5.5 Extensions

The baseline model assumes that each spouse's offer arrival rate is independent of the other's employment status. In practice, offer arrival rates can change through changes in search behaviors when the partner is employed. The searching spouse may reduce effort, lowering the arrival rate, or may benefit from the partner's job network, raising it. I therefore consider an extension in which arrival rates depend on the spouse's employment status, adding four additional parameters that capture these complementarities. Full details are provided in Appendix B.5.

Table A10 presents the new sets of moments used for estimation, and Table A11 presents the estimates of the 14 parameters. There are several takeaways from the new set of estimates: First, the parameters governing arrival rates when spouses are employed are all negative, though not precisely estimated, indicating that having an employed spouse reduces the search effort of the unemployed spouse. Second, θ_m^o is close to 0 while θ_f^o is -0.665, indicating that female displaced workers with an employed spouse is even less likely to search for outside jobs. Third, with the extended model, the remaining female weight β is estimated to be larger (0.456 in the extended model versus 0.386 in the baseline model). This suggests that part of the unequal weighting of female earnings within household is reflected in the fact that women are less likely to search for jobs when their spouses are employed.

6 Quantitative Analysis

Having estimated the model, I now use it to quantify the mechanisms underlying gender gaps in employment and wages. The analysis addresses two broad questions: Which frictions contribute to the gender gaps? How do technological changes that enable alternative work arrangements—especially those altering mobility or household constraints—affect these gaps?

6.1 Decomposing the Gender Gaps

6.1.1 Effect of Co-location Frictions on Gender Inequality

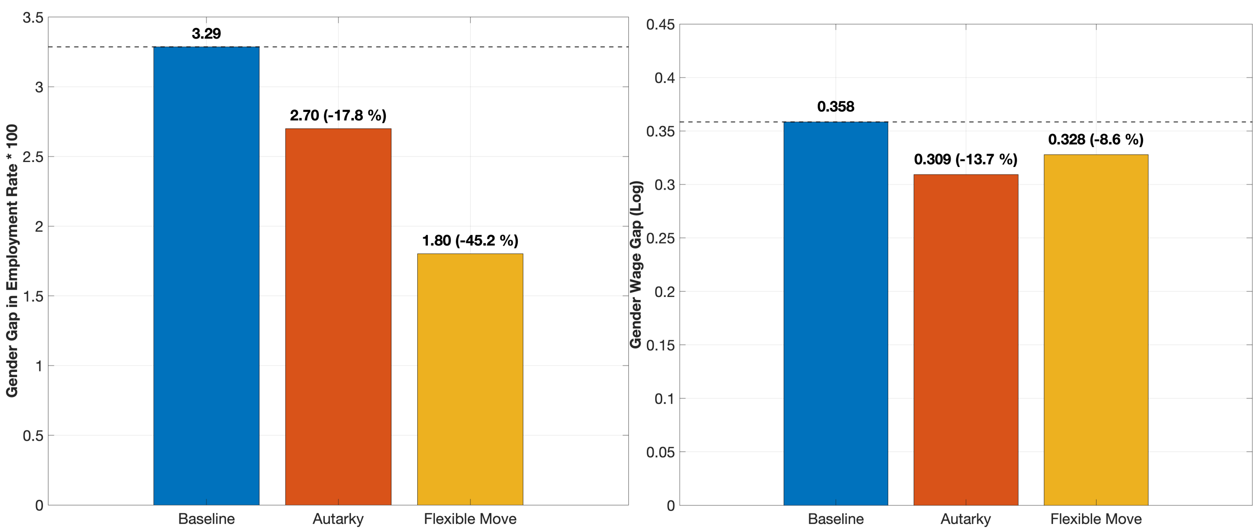
The first set of counterfactuals focuses on migration, the main new channel in my model. As discussed in the model section, migration has a direct impact on worker's labor market outcomes by expanding job opportunities, but it also generates spousal career interruptions. To quantify the contribution of co-location frictions to gender gaps, I consider two extreme scenarios: (1) **Autarky**: there are no outside offers and no migration decisions (Scenario 1), and (2) **Flexible Move**: an ideal world in which spouses can always keep their jobs while moving. Therefore, co-location frictions are removed but moving costs remain. (Scenario 2).

Scenario 1: Autarky. As shown in Proposition **??**, the household problem collapses to two independent single-agent search problems. Figure 7 shows steady-state gender gaps in employment (panel a) and wages (panel b), with the numbers over the bars representing the difference between male and female outcomes. Using the estimates presented in the previous section, the baseline model generates a gender employment gap of 3.3 percent and a gender wage gap of 35.8 log points. In the data, the actual gender gaps for these dual-earner couples are 10 percent for employment and 42 log points for wages. Therefore, my model can explain around 33% of the gender employment gap and 85% of the gender wage gap.

Shutting down the migration channel (orange bar) reduces the gender employment gap to 2.7 percent, corresponding to a 17.8% reduction relative to the baseline. Additionally, it reduces the gender wage gap from 35.8 log points to 30.9 log points, a 13.7% decline. These reductions indicate that men benefit more from having outside options: migration effectively adds a second "wage ladder" that men climb more readily than women because of better underlying labor market opportunities.

Scenario 2: Flexible Move. I remove the co-location constraint by allowing spouses to retain their jobs when the other accepts an outside offer, while migration costs remain. This counterfactual isolates the role of co-location frictions from other labor market asymmetries. The yellow bars in Figure 7 show the steady-state gender gap in employment and wages.

Removing the co-location frictions reduces the gender employment gap by nearly half from 3.3 to 1.67 percent, much more than removing migration (Scenario 1). By relaxing the spousal employment constraint, households can exploit outside opportunities without incurring costly career interruptions. Because women are more likely to be the "tied-movers" and "tied-stayers", they benefit disproportionately from the removal of co-location frictions. Turning to wages, removing co-location frictions reduces the gender wage gap from 35.8 to 32.8 log points (an 8.6% reduction). When spousal job loss is no longer a constraint, women can better capitalize on outside offers, narrowing but not eliminating the wage gap.



(a) Gender Employment Gap

(b) Gender Wage Gap

Figure 7: Effect of Migration on Steady State Gender Gaps

Notes: This figure presents the steady state gender gap in employment (left panel) and wages (right panel). The blue bars are outcomes from the baseline model, the orange bars present counterfactual outcomes when migration channel is shut down by removing outside offers (Scenario 1), and the yellow bars show the counterfactual outcomes when household co-location frictions are removed by letting workers keep their jobs when their spouses are moving for outside offers (Scenario 2). Number on each bar corresponds to the value of the gap, and the numbers in parenthesis show percentage changes relative to the baseline.

Comparing Scenarios 1 and 2 reveals two distinct forces. In Autarky, the wage gap narrows mainly through a leveling-down effect: men lose access to outside ladders. In Flexible Move, the narrowing reflects a catch-up effect: women no longer suffer losses as tied movers and tied stayers. We can see that the leveling-down effect of complete Autarky has a bigger impact on the wage gap than the catch-up effect of Flexible Move. This suggests that the co-location frictions are only one part of why men benefit more from migration. The underlying market frictions persist even when the household constraint is removed. For example, men have a higher outside offer arrival rate and better offer distribution than women. Nevertheless, these results align closely with empirical evidence that household co-location frictions have a larger impact on married women than married men.

6.1.2 Labor Market Frictions and Unequal Weighting

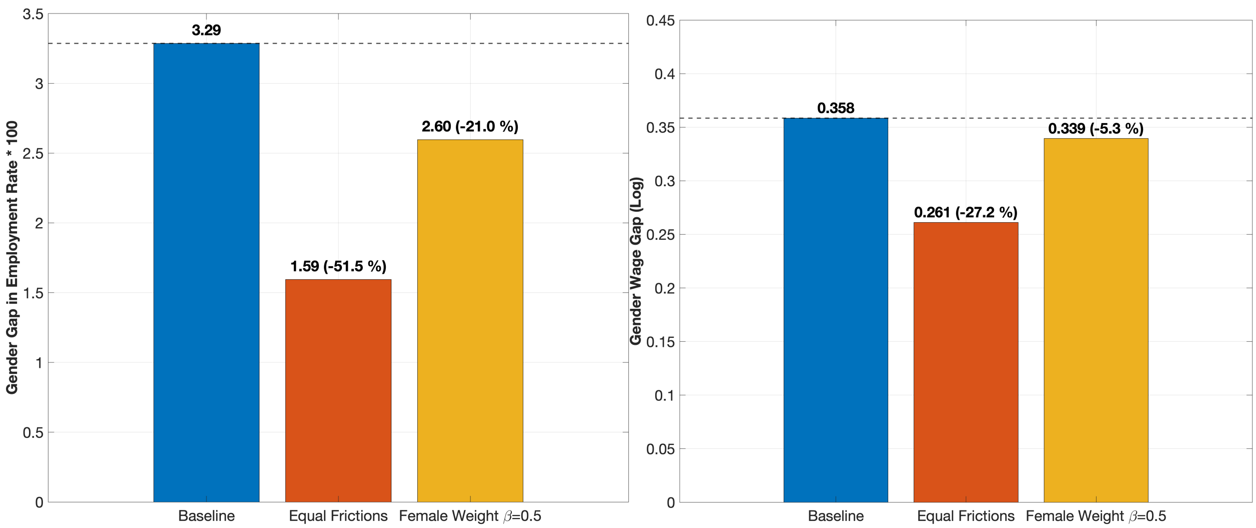
This section evaluates two additional channels in the model: gender differences in labor market opportunities, as captured by offer arrival rates and destruction rates, and unequal weighting of women's income within-household. Both mechanisms have been discussed separately in prior work using different frameworks (Faberman et al., 2025; Jayachandran et al., 2024), but here they are embedded jointly in a unified household search framework. I consider two counterfactuals: (3) equalizing men's and women's labor market frictions, and (4) assigning equal intra-household weight to both spouses.

Scenario 3: Equal Frictions. In the baseline, married women face lower inside and outside offer arrival rates and higher job destruction rates than married men. These differences likely reflect a combination of within-household specialization in search effort and demand-side constraints that limit women's job opportunities. Assigning women the same rates as men isolates the effect of asymmetric frictions.

Equalizing labor market frictions for men and women reduces gender inequality. Figure 8 presents the counterfactual gender gap in employment (Panel a) and wages (Panel b). The first bars (in blue) in both graphs present results from the baseline estimates. When equalizing men's and women's labor market frictions (orange, middle bars), the gender employment gap falls from 3.3 to 1.6 p.p., a 51.5% reduction, while the gender wage gap declines by 27%. These results underscore that differential job-finding and separation rates are key contributors to gender inequality.

Scenario 4: Equal Weighting. The final counterfactual equalizes the intra-household weight on female income, setting $\beta = 0.5$. β governs a household's valuation of the wife's income and captures factors such as household preferences and gender norms. When $\beta < 0.5$, women's earnings are de-emphasized, lowering the household's willingness to accept transitions that advance the wife's career, especially those requiring migration. Unlike market frictions, household weighting may be more directly shaped by policy making such as family leave policies and childcare subsidies.

Equal weighting narrows the employment gap from 3.3 to 2.6 percent (a 21% reduction) and the wage gap from 35.8 to 33.9 log points (a 5.3% reduction). When female weight is lower, the probability of having an outside offer that can justify a spousal quit is even smaller. Therefore, only inside offers matter. When female weight increases, outside offers become more relevant, which is equivalent to having an increase in the offer arrival rates for women. This increases the reservation wages and therefore their steady-state wages. Overall, gender differences in labor market frictions account for a larger share of the gender gaps than unequal weighting within household.



(a) Gender Employment Gap

(b) Gender Wage Gap

Figure 8: Effect of Labor Market Frictions and Weighting on Steady-State Gender Gaps
Notes: This figure presents the steady-state gender gap in employment (left panel) and wages (right panel). The blue bars are outcomes from the baseline model. The orange bars present counterfactual outcomes when equalizing labor market frictions by assigning offer arrival rates and job destruction rates of married men to married women, keeping other parameters unchanged. The yellow bars show the counterfactual outcomes of equal weighting households by setting female weight $\beta = 0.5$ and keeping other parameters at their estimated values. The number on each bar represents the corresponding value of the gap, and the numbers in parenthesis show percentage changes relative to the baseline.

6.2 Availability of Remote Work

Finally, I assess the implications of remote work through the lens of my model. Let γ denote the share of outside job offers that are remote. A remote offer is effectively treated as a local offer: accepting it does not require household migration or induce spousal job loss. With probability $1-\gamma$, the offer remains a traditional outside offer. The effective inside and outside arrival rates become

$$\hat{\alpha}_g^i = \alpha_g^i + \gamma * \alpha_g^o, \quad \hat{\alpha}_g^o = (1-\gamma) * \alpha_g^o,$$

and a key strength of this formulation is that the total number of offers arriving from both inside and outside locations remains constant. This allows me to isolate the effect of remote work's flexibility rather than conflating it with more or fewer opportunities.

Remote work affects the search behavior of different types of workers within households. First, it benefits tied-movers by allowing them to keep their employment upon moving, similar to the Flexible Move counterfactual. Second, it also supports tied-stayers by enabling them to accept outside offers without moving, saving both the spousal income and the migration cost. As women are much more likely than men to be tied-movers and tied-stayers, the relaxation of co-location constraints implies larger gains for them. This is the **liberation effect** (disproportionately benefiting women). At the same time, men enjoy higher baseline arrival rates and more favorable offers; remote work may amplify their wage advantage by expanding their set of acceptable jobs. I label this force as the **competition effect** (favoring men). The net effect on gender gaps is therefore ambiguous.

Migration Responses. Figure 9 shows that for both men and women, annual migration rates decline sharply as γ increases, since workers now have access to more outside job offers that do not require relocation. The drop is steeper for men, whose baseline migration rate (15.3%) exceeds women's (8.9%). Therefore, remote work compresses the gaps between male-initiated and female-initiated migrations for married households.

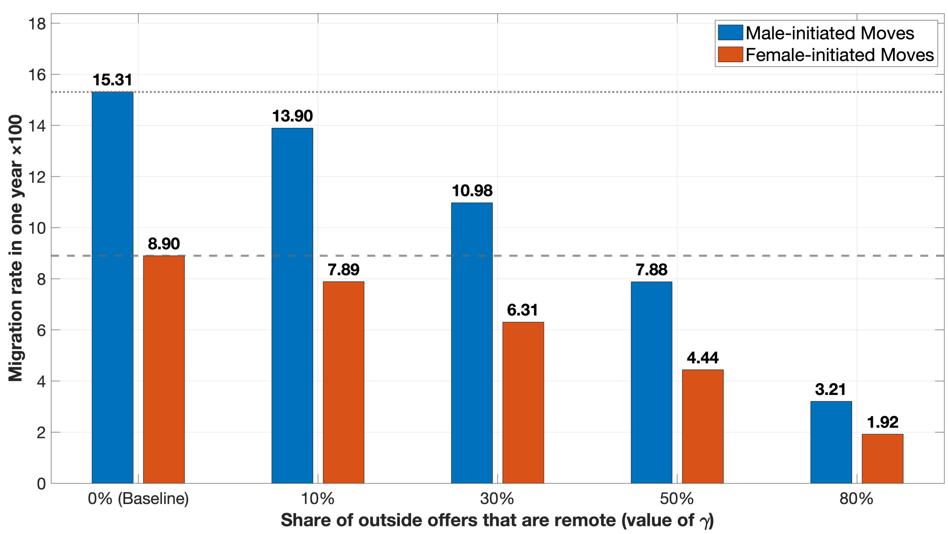


Figure 9: Probability of Moving One Year from Job Loss by Remote Share

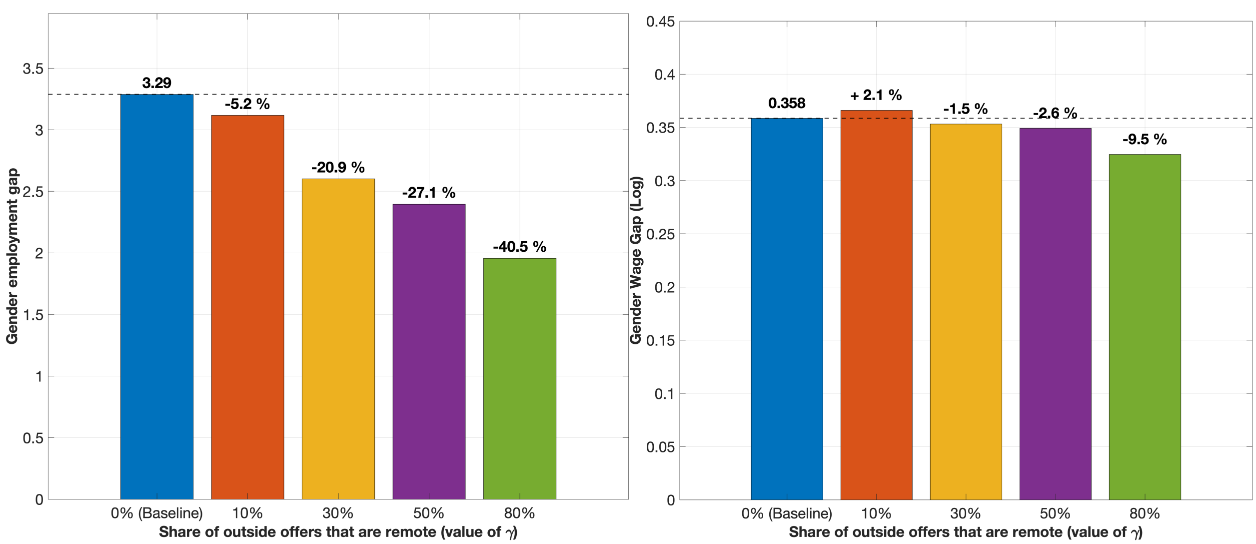
Notes: This figure presents male (blue) and female (red) initiated annual migration rates under different values of γ, the share of outside offers that are remote. The dotted horizontal lines indicate the values of the baseline migration rate for men and women, respectively.

Employment and Wage Effects. Remote work reduces the instances of forced quits for both genders and particularly benefits women. As shown in Panel (a) of Figure 10, the gender employment gap narrows steadily with remote job availability: increasing γ from 0 to 80% reduces the employment gap by 40% relative to the baseline.

Panel (b) of Figure 10 reports the corresponding gender wage gap by remote share. Echoing the discussion above, Panel (b) shows a more nuanced wage response: remote work has non-monotonic effects on the steady-state gender wage gap. At low levels of remote work ($\gamma = 10\%$), the competition effect dominates, slightly widening the wage gap (+2.1%). As γ rises, however, the liberation effect strengthens: women increasingly capitalize on remote offers, and the gender wage gap narrows by nearly 10% at $\gamma = 80\%$.

The share of remote work has increased dramatically since the pandemic, globally, from 10% in 2019 to 28% in 2023.[16] In some industries, this share reached more than 50%. Mapping to the results above with $\gamma = 10\% - 30\%$, this imply that there could be a reduction of 21-27% in gender employment gap and 1.5-2.6% in gender wage gap.

Taken together, these results suggest that remote work availability has the potential to mitigate the negative effects of co-location frictions and promote gender equity in the labor market, especially by reducing women's employment disadvantage. Remote work effectively relaxes household co-location frictions, enabling women—who are more constrained by spousal ties—to access outside opportunities without forcing a spousal quit.



(a) Gender Employment Gap

(b) Gender Wage Gap

Figure 10: Steady State Gender Gap

Notes: Left panel presents the steady-state gender gap in employment rate, and right panel presents the steady state gender wage gap. The numbers at the top of each bar is the percentage changes relative to the baseline. The dotted horizontal lines indicate the values of the baseline.

[16] Report from Payscale: https://www.payscale.com/featured-content/remote-work.

7 Conclusion

This paper shows that co-location frictions—constraints that arise when moving for one spouse's job come at the cost of the other's—play an important role in shaping migration decisions and sustaining gender inequality in the labor market. Using evidence from displaced workers in the CPS, I document large and systematic gender asymmetries in geographic mobility: households are far more likely to relocate after the husband's job loss than after the wife's. These asymmetries translate into unequal labor-market outcomes. Although relocation mitigates the earnings loss from job displacement, the gains accrue disproportionately to men, while women are more likely to be trailing spouses and experience persistent employment and wage penalties.

The household search model developed in this paper provides a unified framework for interpreting these patterns. By jointly modeling job offers across locations, household migration decisions, and intra-household weighting of income, the model quantifies the contribution of co-location frictions to observed gender gaps. The estimates imply that co-location frictions account for roughly half of the gender employment gap and about 9 percent of the gender wage gap. Unequal weighting of women's earnings in household decision-making contributes modest but nontrivial parts of the gender gaps as well. Introducing remote work—effectively transforming outside offers into local ones—substantially improves women's employment outcomes and modestly narrows the wage gap. Together, these exercises reveal that both market and household constraints jointly sustain gender disparities following job loss.

More broadly, this study underscores that understanding gender inequality in modern labor markets requires modeling the household as a joint decision-making unit. Labor mobility, wage dynamics, and the geography of opportunity are deeply intertwined with family structure and social norms. Policies that reduce the costs of dual-career coordination—such as promoting remote work, improving access to childcare, or designing relocation and unemployment benefits that account for spousal employment—can enhance equity in labor markets.

Future work will extend the model to incorporate on-the-job search and exogenous migration shocks. These extensions will allow the framework to capture job-to-job transitions and moves for non-employment reasons, providing a richer account of household mobility and its role in shaping gender inequality.

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Appendices

A Additional Empirical Analysis

A.1 Tables

Table A1: Data linkage to construct household level panel

Time	Data Source
$t-1$	$DWS_t : DW, \quad MarchSupp_t : Sp$
t	$DWS_t : DW, \quad ORG_t : Sp$
$t+1$	$DWS_{t+1} : DW, \quad ORG_{t+1} : Sp$

Table A2: Treated and Control after Propensity Score Matching

	Female			Male		
	Control	Treated	Diff.	Control	Treated	Diff.
Weekly Wages - Lost Job (100USD)	4.79	4.83	-0.03	7.63	7.61	0.03
			(0.06)			(0.07)
Lost Job Was Full-Time	0.76	0.76	-0.00	0.95	0.95	0.00
			(0.01)			(0.00)
Share College Degree	0.24	0.25	-0.01	0.23	0.23	-0.00
			(0.01)			(0.01)
Average Age	40.92	40.89	0.03	40.82	40.95	-0.12
			(0.17)			(0.14)
Children Under 5	0.19	0.19	0.01	0.28	0.27	0.01
			(0.01)			(0.01)

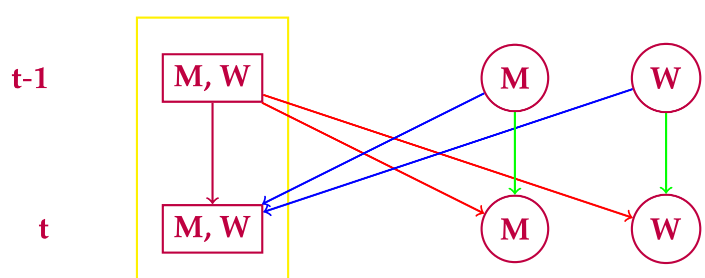


Table A3: Probability of Changing Occupation and industry

	Married		Married+Unmarried		Married+NeverMarried	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Displaced	0.020***	0.047***	0.044***	0.050***	0.050***	0.050***
	(0.005)	(0.004)	(0.007)	(0.007)	(0.011)	(0.009)
Displaced*Married			-0.023***	-0.003	-0.030**	-0.003
			(0.008)	(0.008)	(0.012)	(0.010)
Control Mean	0.037	0.043	0.047	0.053	0.045	0.050
Covariates	✓	✓	✓	✓	✓	✓
N	10752	20301	20714	31761	15207	27262

Notes: CPS DWS and March Supplement 1990-2020. Column 1-4 are estimated on the married sample, and column 5-6 are on the unmarried sample. "Female" and "Male" refer to the gender of the displaced worker. Covariates include quadratics of age, race indicator, college indicator, indicator for children, weekly wages, full-time status, indicator for public sector, 1-digit industry, and 1-digit occupation for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Standard errors are clustered at the matched pair level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Probability of Migration After Job Loss - by Presence and Age of Children

	Ages 25-40		Ages 41-60		Before 2000		After 2000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	F	M	F	M	F	M	F	M
Displaced	0.046***	0.056***	0.029***	0.039***	0.032***	0.045***	0.040***	0.051***
	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)
Displaced*Married	-0.020*	-0.004	-0.018**	0.003	-0.023**	0.010	-0.017*	-0.012
	(0.011)	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.009)	(0.010)
Control Mean	0.061	0.070	0.028	0.031	0.053	0.061	0.039	0.046
Covariates	✓	✓	✓	✓	✓	✓	✓	✓
N	14045	19430	12265	14634	12189	16965	14121	17099

Notes: CPS DWS and March Supplement 1982-2020. Sample include both married and single workers. Column 1,3,5,7 are estimated on the female sample (F), and column 2,4,6,8 are estimated on the male sample (M). Control mean reports mean annual migration rate for the non-displaced control group. Covariates include quadratics of age, race indicator, college indicator, indicator for children, weekly wages, full-time status, indicator for public sector, and industry and occupation dummies for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Standard errors are clustered at the matched pair level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Probability of Migration After Job Loss

	Female Displaced		Male Displaced	
	(1)	(2)	(3)	(4)
	Below Median	Above Median	Below Median	Above Median
Displaced	0.004	0.013	0.047***	0.039***
	(0.009)	(0.008)	(0.009)	(0.008)
Control mean	0.049	0.039	0.049	0.039
Covariates	✓	✓	✓	✓
N	4009	4010	6063	6061

Notes: CPS DWS and March Supplement 1982-2020. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Probability of Changing Occupation and industry

	Change Occupation		Change Industry	
	(1)	(2)	(3)	(4)
	Female	Male	Female	Male
Displaced	0.429***	0.433***	0.436***	0.469***
	(0.013)	(0.010)	(0.013)	(0.010)
Displaced*Moved	0.005	-0.103***	-0.077	-0.176***
	(0.057)	(0.035)	(0.059)	(0.039)
Moved	0.037*	0.066***	0.084***	0.126***
	(0.021)	(0.018)	(0.031)	(0.024)
Control Mean	0.036	0.031	0.094	0.087
Covariates	✓	✓	✓	✓
N	9223	14210	9183	14192

Notes: CPS DWS and March Supplement 1990-2020. Change Occupation is an indicator for finding employment in a different 2-digit occupation group from the previous job. Change Industry is an indicator for finding employment in a different 2-digit industry group from the previous job. Covariates include quadratics of age, race indicator, college indicator, indicator for children, weekly wages, full-time status, indicator for public sector, 1-digit industry, and 1-digit occupation for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Raw Weekly Wages - Full-time Workers Only

	Married				Unmarried	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Displaced	-282.5***	-326.7***	-286.3***	-340.9***	-258.3***	-327.6***
	(8.3)	(8.8)	(8.3)	(9.0)	(8.7)	(9.5)
Displaced*Moved			92.0**	194.1***	102.0***	79.0**
			(45.4)	(36.3)	(28.6)	(31.5)
Moved			-69.1***	-40.8*	-75.5***	-18.2
			(26.2)	(22.0)	(15.7)	(19.2)
Control Mean	566.9	808.4	566.9	808.4	535.0	629.3
Covariates	✓	✓	✓	✓	✓	✓
N	8784	15506	8784	15506	8435	9395

Notes: CPS DWS and March Supplement 1990-2020. Column 1-2 show results on the sample without children, column 3-4 for those with young children under age 5, and column 5-6 for those with children over age 5. Control mean reports mean annual migration rate for the non-displaced control group. Covariates include quadratics of age, race indicator, college indicator, indicator for children, weekly wages, full-time status, indicator for public sector, 1-digit industry, and 1-digit occupation for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Raw Weekly Wages - By Presence and Age of Children

	No Child		Have Children	
	(1)	(2)	(3)	(4)
	Female	Male	Female	Male
Displaced	-256.4***	-379.1***	-232.4***	-304.8***
	(12.8)	(15.8)	(8.3)	(10.1)
Displaced*Moved	47.6	231.6***	104.4**	183.9***
	(57.9)	(71.2)	(50.5)	(39.4)
Moved	-47.6	-8.4	-93.7***	-59.1**
	(35.7)	(39.5)	(26.8)	(25.8)
Control Mean	532.0	767.8	484.1	792.6
Covariates	✓	✓	✓	✓
N	3843	4602	7630	11769

Notes: CPS DWS and March Supplement 1990-2020. Column 1-2 show results on the sample without children, column 3-4 for those with young children under age 5, and column 5-6 for those with children over age 5. Control mean reports mean annual migration rate for the non-displaced control group. Covariates include quadratics of age, race indicator, college indicator, indicator for children, weekly wages, full-time status, indicator for public sector, 1-digit industry, and 1-digit occupation for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Own and Spousal Earnings Changes by Moving Status

	Female Displaced			Male Displaced		
	(1)	(2)	(3)	(4)	(5)	(6)
	HH Total	Female(DW)	Male(Sp)	HH Total	Female(Sp)	Male(DW)
Displaced	-223.7***	-223.3***	-3.1	-315.1***	-18.0*	-298.7***
	(25.3)	(15.1)	(17.0)	(22.4)	(10.2)	(19.4)
Displaced*Moved	284.5*	114.8	125.8	258.1**	-46.8	283.6***
	(154.5)	(106.6)	(89.1)	(107.1)	(41.0)	(98.5)
Moved	-64.0	-34.7	-52.3	-94.3	14.2	-81.5
	(107.7)	(56.0)	(62.9)	(78.8)	(33.0)	(71.3)
Control mean	1262.1	481.9	777.4	1178.0	413.6	780.5
Covariates	✓	✓	✓	✓	✓	✓
N	1817	2070	1879	2709	2863	2883

Notes: CPS DWS and March Supplement 1990-2020. DW: the displaced worker him or herself. Sp: spouse of the displaced worker. Covariates include quadratics of age, race indicator, college indicator, indicator for children, weekly wages, full-time status, indicator for public sector, 1-digit industry, and 1-digit occupation for the lost job. All regressions include year and state FE, and are weighted using individual survey weight. Robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Figures

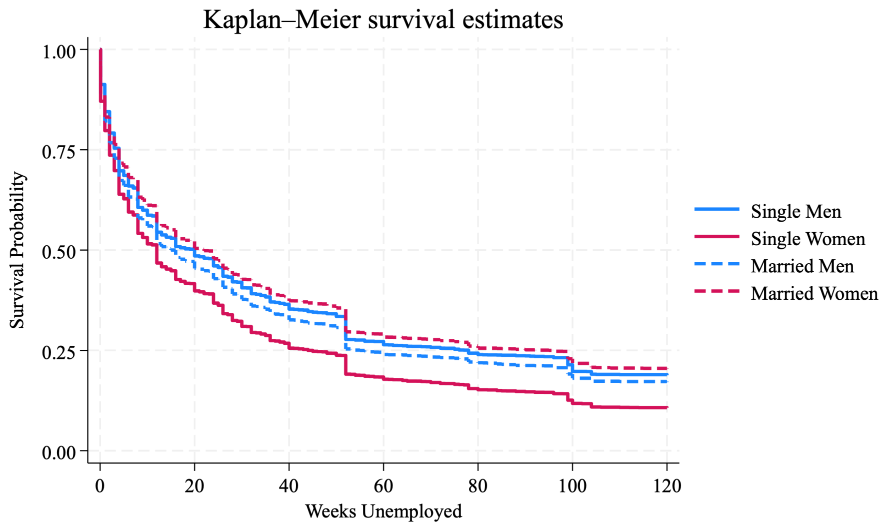


Figure A1: Survival Probability - By Gender and Marital Status
Notes: Sample includes workers who lost their jobs in the previous three years. This figure shows the Kaplan Meier survival estimates by gender and by marital status: married women (red dash), married men (blue dash), single women (red solid), single men (blue dash). The lines represent the probability of remaining unemployed against unemployment duration.

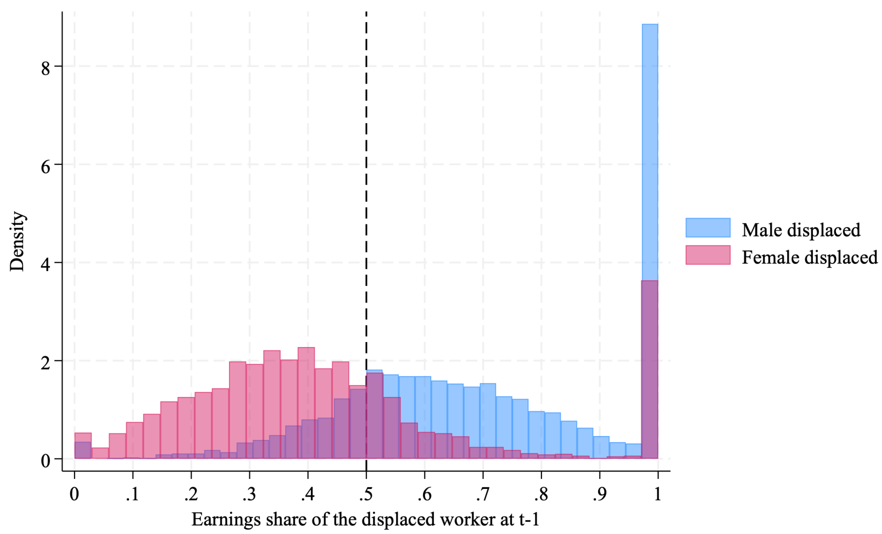
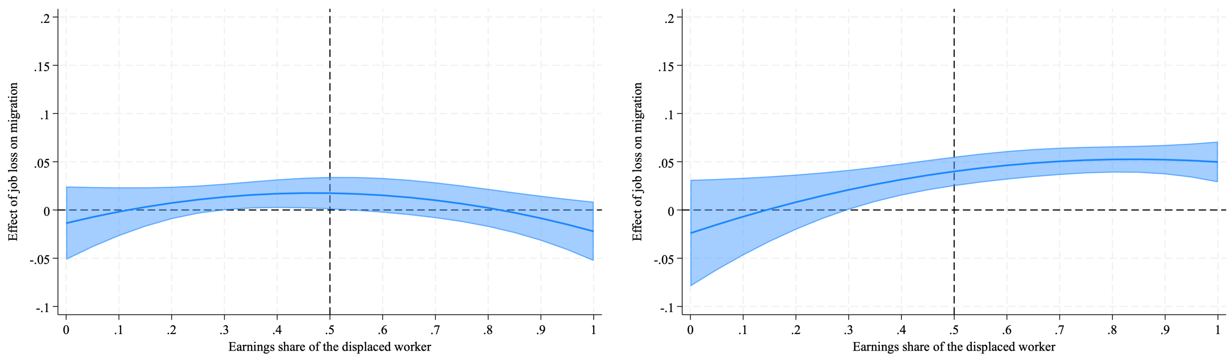


Figure A2: Earnings Share of the Displaced Worker by Gender
Notes: $EarnShare = EarnDisplaced/(EarnDisplaced + EarnSpouse)$. This figure shows the distribution of actual earnings shares within household of the displaced worker in $t-1$, separately for men (blue bars) and women (pink bars).



(a) Female (b) Male

Figure A3: Probability of Moving After Job Loss by Earnings Share - Nonlinear

Notes: This figure presents predicted probability of moving after job loss for female displaced workers (Panel a) and male displaced workers (Panel b). Estimates are obtained by estimating Equation 3 using actual earnings shares of displaced workers, and additionally adding quadratic terms of earnings shares as well as its interaction with the dummy for displaced.

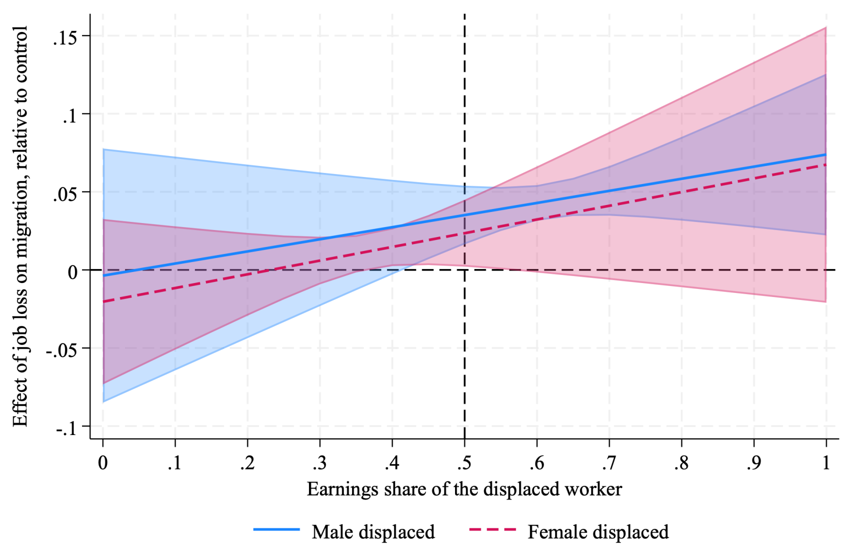


Figure A4: Probability of Moving by Earnings Share in $t-1$

Notes: This figure presents the predicted probability of moving after job loss against the predicted earnings share for male-headed (blue) and female-headed (red) households, relative to the control households. Probabilities are predicted from Equation 3.

A.3 Predict Earnings Potential

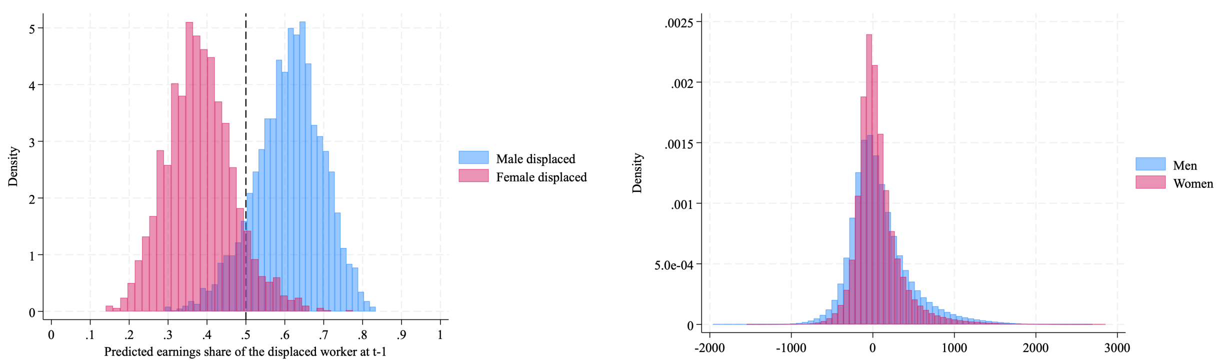
To estimate earnings potential based on observable characteristics, I use a pooled sample constructed from the Merged Outgoing Rotation Group (ORG) and the March Supplement of the Current Population Survey. I regress weekly earnings on education levels interacted with age quadratics, as well as other demographic and job-related characteristics. Specifically, I estimate the following specification:

$$WeekEarn_{it} = \sum_{e} \mathbb{1}(Educ = e)(\gamma_{e,1} Age_{it} + \gamma_{e,2} Age_{it}^2) + \Gamma X_{it} + \lambda_t + \epsilon_{it}$$

where $Educ$ takes on 32 distinct values. The vector X_{it} includes indicators for race, full-time status, presence of children, occupation, industry, state, and year. Using the estimated coefficients, I compute predicted weekly earnings for each individual based on their education-age profile and other observable characteristics:

$$\overline{WeekEarn}_{it} = \sum_{e} \mathbb{1}(Educ = e)(\hat{\gamma}_{e,1} Age_{it} + \hat{\gamma}_{e,2} Age_{it}^2) + \hat{\Gamma} X_{it} + \hat{\lambda}_t$$

To check the accuracy of prediction, for each worker, I calculate the difference between actual earnings and predicted earnings based on observables. Figure A5b presents the distribution of the prediction errors by gender. We can see that both distributions are concentrated around 0, though the error can be as large as 2000. Earnings prediction is slightly more accurate for women than for men.



(a) Predicted Earnings Distributions

(b) Prediction Errors

Figure A5: Predicted Earnings Shares by Gender

Finally, I match the predicted earnings with individuals in the main sample based on the year of job loss to ensure consistency between predicted earnings potential and the timing of displacement.

B Model

B.1 Proof of Proposition 1

The value function for an employed single individual earning wage w is:

$$r\Omega_g^{sin}(w) = \nu(w) + \delta_g[U_g^{sin} - \Omega_g^{sin}(w)]$$

Rearranging the terms, we have:

$$\Omega_g^{sin}(w) = \frac{\nu(w) + \delta_g U_g^{sin}}{r + \delta_g} \tag{10}$$

Since U_g^{sin} is a constant, $\Omega_g^{sin}(w)$ is increasing in w. Therefore, optimal job acceptance follows a reservation wage strategy. Let R_g^i and R_g^o denote the reservation wages for offers from locations i and o, respectively. These reservation wages are defined by the following conditions:

$$\Omega_g^{sin}(R_g^i) = U_g^{sin}, \quad \Omega_g^{sin}(R_g^o) = U_g^{sin} + \psi_g$$

Therefore,

$$\Omega_g^{sin}(R_g^i) = \frac{\nu(R_g^i) + \delta_g U_g^{sin}}{r + \delta_g} = U_g^{sin}, \quad \Omega_g^{sin}(R_g^o) = \frac{\nu(R_g^o) + \delta_g U_g^{sin}}{r + \delta_g} = U_g^{sin} + \psi$$

$$U_g^{sin} = \frac{\nu(R_g^i)}{r} = \frac{\nu(R_g^o) - \psi(r + \delta_g)}{r}$$

Plugging in Equation (10) in the value of unemployment:

$$\begin{aligned}
rU_g^{sin} &= \nu(b_g) + \alpha_g^i \int_{R_g^i} (\Omega_g^{sin}(w) - U_g^{sin}) dF_g(w) + \alpha_g^o \int_{R_g^o} (\Omega_g^{sin}(w) - U_g^{sin} - \psi) dF_g(w) \\
&= \nu(b_g) + \alpha_g^i \int_{R_g^i} (\frac{\nu(w) - rU_g^{sin}}{r + \delta_g}) dF_g(w) + \alpha_g^o \int_{R_g^o} (\frac{\nu(w) - rU_g^{sin}}{r + \delta_g} - \psi) dF_g(w)
\end{aligned}$$

Integrating by parts, the reservation wages for inside offers is:

$$\begin{aligned}\nu(R_g^i) &= \nu(b_g) + \frac{\alpha_g^i}{r+\delta_g}\int_{R_g^i}(\nu(w)-\nu(R_g^i))dF_g(w) + \frac{\alpha_g^o}{r+\delta_g}\int_{R_g^o}(\nu(w)-\nu(R_g^o))dF_g(w)\\ &= b_g + \frac{\alpha_g^i}{r+\delta_g}\int_{R_g^i}\nu'(w)[1-F_g(w)]dw + \frac{\alpha_g^o}{r+\delta_g}\int_{R_g^o}\nu'(w)[1-F_g(w)]dw\end{aligned}$$

Similarly, the outside reservation wage is given by:

$$\nu(R_g^o) = \nu(b_g) + \frac{\alpha_g^i}{r+\delta_g}\int_{R_g^i}\nu'(w)[1-F_g(w)]dw + \frac{\alpha_g^o}{r+\delta_g}\int_{R_g^o}\nu'(w)[1-F_g(w)]dw + (r+\delta_g)\psi_g$$

and the outside reservation wages will be higher than the inside reservation wage.

B.2 Law of Motion for Married Household

Assume a unit population of joint households. There are four types of households depending on the labor market status of the husband and the wife. The mass of joint households who are (i) dual-nonemployed, s_U, (ii) male-headed worker-searcher households, s_Ω^m, (iii) female-headed searcher-worker households s_Ω^f, (iv) dual-employed, s_T, must sum to one. Specifically, we have,

$$s_U + s_\Omega^m + s_\Omega^f + s_T = 1.$$

In steady state, the law of motion for s_U satisfies the following equation

$$\delta_m s_\Omega^m + \delta_f s_\Omega^f = \{\overbrace{\alpha_m^i[1-F_m(R_m^{1i})] + \alpha_m^o[1-F_m(R_m^{1o})]}^{S_U^m} + \overbrace{\alpha_f^i[1-F_f(R_f^{1i})] + \alpha_f^o[1-F_f(R_f^{1o})]}^{S_U^f}\}s_U,$$

where the right-hand side (RHS) represents outflows from dual-nonemployment to male-headed households and female-headed households, both within the current location and to the outside location. Outflows occur when a member of the household accepts a job offer that is above her inside reservation wage or outside reservation wage. The left-hand side (LHS) represents all the inflows, which occur when the employed worker in a worker-searcher or searcher-worker household is exogenously separated. The steady state share of dual-nonemployed households is given by

$$s_U = \frac{\delta_m s_\Omega^m + \delta_f s_\Omega^f}{S_U^m + S_U^f} \tag{11}$$

Let $G^m(w)$ be the cumulative distribution function that a male-headed worker-searcher household earns a wage $w' < w$ and $g^m(w)$ as the associated with probability density function. $G^f(w)$ and $g^f(w)$ are defined in similar ways for the female-headed households. Analogously, $G^T(w_m, w_f)$ is the cumulative distribution function for dual-employed households in which the husband earns w_m and the wife earns w_f, with $g^T(w_m, w_f)$ as the PDF. Then the mass of male-headed worker-searcher households in which the male worker is earning a wage w is given by

$$
\begin{aligned}
&\{\alpha_m^i[F_m(w) - F_m(R_m^{1i})] + \alpha_m^o[F_m(w) - F_m(R_m^{1o}]\}s_U + \delta_f \left\{ \int_{\underline{w}}^{w} \int_{\underline{w}}^{\bar{w}} g^T(z,y)dydz \right\} s_T \\
&+ \alpha_m^i \left\{ \int_{\underline{w}}^{w_f^c} \mathbb{1}(w > \phi^m(y))[F_m(w) - F_m(\phi^m(y))]g^f(y)dy \right\} s_\Omega^f \\
&+ \alpha_m^o \left\{ \int_{\underline{w}}^{\bar{w}} \mathbb{1}(w > R_{3o}^m(y))[F_m(w) - F_m(R_{3o}^m(y))]g^f(y)dy \right\} s_\Omega^f \\
&= \delta_m G^m(w)s_\Omega^m + \alpha_f^i \left\{ \int_{\underline{w}}^{w} [1 - F_f(\phi^f(z))]g^m(z)dz \right\} s_\Omega^m + \alpha_f^o \left\{ \int_{\underline{w}}^{w} [1 - F_f(R_f^{3o}(z))]g^m(z)dz \right\} s_\Omega^m
\end{aligned}
$$

The first two terms on the LFH describe inflows from the dual-nonemployed households to male-headed households when the male member accepts an inside or outside offer that are above the corresponding reservation wages. The third term represents inflows from dual-employed households when the wife is exogenously separated from her job. The fourth and the fifth terms capture inflows from female-headed households when the husband accepts an inside or outside offer that induces the breadwinner cycle. On the RHS, the first term describes the outflow to dual-nonemployed households when the husband is displaced from his job. The second term describes the outflow to either dual-worker households or female-headed searcher-worker households when the wife receives an inside offer thats above her reservation wage. Finally, the last term captures the breadwinner cycle when the wife accepts an outside offer and the household move to become a female-headed searcher-worker household. Evaluating this equation at $w = \bar{w}$, we arrive at the measure of male-headed households

$$
s_\Omega^m = \frac{S_U^m s_U + \delta_f s_T + \left\{ \alpha_m^i \int_{\underline{w}}^{w_f^c} [1 - F_m(\phi^m(y))]g^f(y)dy + \alpha_m^o \int_{\underline{w}}^{\bar{w}} [1 - F_m(R_{3o}^m(y))]g^f(y)dy \right\} s_\Omega^f}{\delta_m + \alpha_f^i \left\{ \int_{\underline{w}}^{\bar{w}} [1 - F_f(\phi^f(z))]g^m(z)dz \right\} + \alpha_f^o \left\{ \int_{\underline{w}}^{\bar{w}} [1 - F_f(R_f^{3o}(z))]g^m(z)dz \right\}} \tag{12}
$$

Similarly, we can derive the steady state measure of female-headed households

$$s_{\Omega}^{f}=\frac{S_{U}^{f}s_{U}+\delta_{m}s_{T}+\left\{\alpha_{f}^{i}\int_{\underline{w}}^{w_{m}^{c}}[1-F_{f}(\phi^{f}(y))]g^{m}(y)dy+\alpha_{f}^{o}\int_{\underline{w}}^{\bar{w}}[1-F_{f}(R_{f}^{3o}(y))]g^{m}(y)dy\right\}s_{\Omega}^{m}}{\delta_{f}+\alpha_{m}^{i}\left\{\int_{\underline{w}}^{\bar{w}}[1-F_{m}(\phi^{m}(z))]g^{f}(z)dz\right\}+\alpha_{m}^{o}\left\{\int_{\underline{w}}^{\bar{w}}[1-F_{m}(R_{3o}^{m}(z))]g^{f}(z)dz\right\}} \tag{13}$$

Next, we can characterize the share of dual-worker households. The mass of dual-employed household earning $(z,y)<(w_m,w_f)$ is given by

$$\alpha_{m}^{i}\int_{w_{m}^{c}}^{w_{f}}\int_{\phi^{m}(y)}^{w_{m}}F_{m}(z)dzg^{f}(y)dy\cdot s_{\Omega}^{f}+\alpha_{f}^{i}\int_{w_{f}^{c}}^{w_{m}}\int_{\phi^{f}(y)}^{w_{f}}F_{f}(z)dzg^{m}(y)dy\cdot s_{\Omega}^{m}=(\delta_{m}+\delta_{f})G^{T}(w_{m},w_{f})s_{T}$$

The LHS captures the inflow to dual-employment status. The first term describes the share of female-headed searcher-worker households currently earning a wage y above the cutoff wage w_m^c such that the household will become a dual-employed household once the husband accepts a wage offer that is above his reservation wage, $\phi^m(y)$. The second term is defined in a similar way but captures the inflow from male-headed worker-searcher households. The RHS describes the outflow from dual-employed households earning wage pair (w_m,w_f) to either male-headed or female-headed households due to exogenous separation.

Evaluating the above at $(w_m,w_f)=(\bar{w},\bar{w})$, we can derive the mass of dual-employed households:

$$s_{T}=\frac{\alpha_{m}^{i}}{\delta_{m}+\delta_{f}}\int_{w_{m}^{c}}^{\bar{w}}[1-F_{m}(\phi^{m}(y)]g^{f}(y)dy\cdot s_{\Omega}^{f}+\frac{\alpha_{f}^{i}}{\delta_{m}+\delta_{f}}\int_{w_{f}^{c}}^{\bar{w}}[1-F_{f}(\phi^{f}(y)]g^{m}(y)dy\cdot s_{\Omega}^{m} \tag{14}$$

The measure of employed males who are in joint households is $s_m=s_T+s_{\Omega}^m$. Let $H^m(w)$ be the cumulative distribution function of males in a joint household earning less than or equal to w, we have:

$$H^{m}(w)s_{m}=G^{m}(w)s_{\Omega}^{m}+\left\{\int_{\underline{w}}^{w}\int_{\underline{w}}^{\bar{w}}g^{T}(z,y)dydz\right\}s_{T}$$

Let $h^m(w)$ be the corresponding probability density function:

$$h^m(w)s_m = g^m(w)s_\Omega^m + \left\{ \int_{\underline{w}}^{\bar{w}} g^T(z,y)dy \right\} s_T$$

B.3 Household flow utility

Suppose individuals have CRRA utility $v(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$ and $\gamma \neq 1$. Then household maximization problem under full income pooling becomes

$$\begin{aligned} \max_{c_m, c_f} \quad & (1-\beta)\frac{c_m^{1-\gamma}-1}{1-\gamma} + \beta\frac{c_f^{1-\gamma}-1}{1-\gamma} \\ s.t. \quad & c_m + c_f = I \end{aligned}$$

where I denotes the total resource of the household (w if working, b if nonemployed).

Optimal consumption bundle is given by:

$$c_m = \left(\frac{1-\beta}{\beta}\right)^{\frac{1}{\gamma}} \frac{I}{1+\left(\frac{1-\beta}{\beta}\right)^{\frac{1}{\gamma}}}, \quad c_f = \frac{I}{1+\left(\frac{1-\beta}{\beta}\right)^{\frac{1}{\gamma}}}$$

Plugging optimal consumptions back to the utility function:

$$\underbrace{\left\{(1-\beta)\left(\frac{1-\beta}{\beta}\right)^{\frac{1-\gamma}{\gamma}}\left(1+\left(\frac{1-\beta}{\beta}\right)^{\frac{1}{\gamma}}\right)^{\gamma-1} + \beta\left(1+\left(\frac{1-\beta}{\beta}\right)^{\frac{1}{\gamma}}\right)^{\gamma-1}\right\}}_{Z(\beta)} \frac{I^{1-\gamma}}{1-\gamma} - \frac{1}{1-\gamma}$$

We can rewrite the dual-searcher's value function as:

$$\begin{aligned} rU =& Z(\beta)\frac{(b_m+b_f)^{1-\gamma}}{1-\gamma} - \frac{1}{1-\gamma} \\ & + \alpha_i^m \int_{R_{1i}^m} (\Omega^m(w) - U)dF^m(w) + \alpha_o^m \int_{R_{1o}^m} (\Omega^m(w) - U - \psi)dF^m(w) \\ & + \alpha_i^f \int_{R_{1i}^f} \{\Omega^f(w) - U, 0\}dF^f(w) + \alpha_o^f \int_{R_{1o}^f} \{\Omega^f(w) - U - \psi, 0\}dF^f(w) \end{aligned}$$

In the flow value part, $Z(\beta)$ and I are not separable. Because of the existence of moving cost ψ, labor market decisions are dependent on the Pareto weight β. $Z(\beta)$ is single-peaked at $\beta = 0.5$, therefore, $\beta = 0.1$ and $\beta = 0.9$ give the same value of $Z(\beta)$ and imply the same set of reservation wages.

B.4 Risk Neutrality and No Migration

When the flow utility is linear and there are no outside offers, the value functions for single workers are as follows:

$$rU_g^{sin} = b_g + \alpha_g^i \int \{\Omega_g^{sin}(w) - U_g^{sin}\}^+ dF_g(w)$$

The value function for an employed single individual earning wage w is:

$$r\Omega_g^{sin}(w) = w + \delta_g[U_g^{sin} - \Omega_g^{sin}(w)]$$

The value functions of the four types of households are:

Dual-unemployed

$$rU = (1-\beta)b_m + \beta b_f + \sum_{g\in\{m,f\}} \alpha_g^i \int \{\Omega_g(w) - U\}^+ dF_g(w)$$

Male-Headed Worker-Searcher Households

$$r\Omega_m(w) = (1-\beta)w + \beta b_f + \delta_m[U - \Omega_m(w)] + \alpha_f^i \int \{T(w, w_f) - \Omega_m(w), \Omega_f(w_f) - \Omega_m(w)\}^+ dF_f(w_f)$$

Female-Headed Worker-Searcher Households

$$r\Omega_f(w) = (1-\beta)b_m + \beta w + \delta_f[U - \Omega_f(w_f)] + \alpha_m^i \int \{T(w_m, w) - \Omega_f(w), \Omega_m(w_m) - \Omega_f(w)\}^+ dF_m(w_m)$$

Dual-Worker Household

$$rT(w_m, w_f) = (1-\beta)w_m + \beta w_f + \delta_m[\max\{\Omega_f(w_f), U\} - T(w_m, w_f)] + \delta_f[\max\{\Omega_m(w_m), U\} - T(w_m, w_f)]$$

We prove by "guess and verify". Define the candidate household values by:

$$\begin{aligned}
U &:= (1-\beta) * U_m^{sin} + \beta * U_f^{sin} \\
\Omega_m(w) &:= (1-\beta) * \Omega_m^{sin}(w) + \beta * U_f^{sin} \\
\Omega_f(w) &:= (1-\beta) * U_m^{sin} + \beta * \Omega_f^{sin}(w) \\
T(w_m, w_f) &:= (1-\beta) * \Omega_m^{sin}(w_m) + \beta * \Omega_f^{sin}(w_f)
\end{aligned}$$

From the dual-unemployed state, the man accepts an inside offer w if $\Omega_m(w) \geq U$. Using the candidate values,

$$\Omega_m(w) - U = \beta * (\Omega_m^{sin}(w) - U_g^{sin})$$

As $\beta > 0$, the man's reservation wage in the household problem equals the single man's reservation wage, and it does not depend on the woman's wage/employment. A similar argument is true for women.

Consider a male-headed household (man employed at wage w, woman unemployed) when the inside market delivers an offer w_f to the woman. The household compares two transitions: dual-employed ($T(w, w_f) - \Omega_m(w)$), and breadwinner cycle with the man quit ($\Omega_f(w_f) - \Omega_m(w)$). Under the candidate value functions above,

$$\begin{aligned} T(w, w_f) - \Omega_m(w) &= \beta(\Omega_f^{sin}(w_f) - U_f^{sin}) \\ \Omega_f(w_f) - \Omega_m(w) &= \beta * (\Omega_f^{sin}(w_f) - U_f^{sin}) + (1 - \beta) * (U_m^{sin} - \Omega_m^{sin}(w)) \end{aligned}$$

Note that as the man accepted the wage to start with, that means wage w exceeds his reservation wage and $\Omega_g^{sin} \geq U_m^{sin}$. Therefore, $U_m^{sin} - \Omega_g^{sin} \leq 0$, and

$$T(w, w_f) - \Omega_m(w) \geq \Omega_f(w_f) - \Omega_m(w)$$

which suggests that the breadwinner cycle will never be triggered.

Finally, when both the man and the woman are employed ($T(w_m, w_f)$), we have $\Omega_m^{sin}(w_m) \geq U_m^{sin}$ and $\Omega_f^{sin}(w_f) \geq U_f^{sin}$. Therefore, $\max\{\Omega_m(w_m), U\} = \Omega_m(w_m)$ and $\max\{\Omega_f(w_f), U\} = \Omega_f(w_f)$. We can then verify that

$$rT(w_m, w_f) = r(1 - \beta) * \Omega_m^{sin}(w_m) + r\beta * \Omega_f^{sin}(w_f),$$

which is consistent with the candidate value function.

B.5 Model Extension: Dependent Offer Arrival Rates

B.5.1 Model set-up

Suppose offer arrival rates depend on the employment status of the spouse. For each $g \in \{m, l\} \times l \in \{i, o\}$, we have:

$$\alpha_g^l(s) = \alpha_g^l \times exp(\theta_g^l \cdot s_{-g})$$

where $s_{-g} \in \{0,1\}$ indicate the employment status of the spouse. While not modeling search effort directly, this specification captures equilibrium changes in the search behaviors of married workers in response to changes in their spouses' employment status.

There are four new parameters $(\theta_m^i, \theta_m^o, \theta_f^i, \theta_f^o)$, and the sign of these parameters was ambiguous. On the one hand, time/childcare constraints may reduce the search effectiveness for the unemployed spouse while the partner is working, leading lower arrival rates ($\theta_g^l < 0$). On the other hand, the employed spouse's job improves local networks, information, and resources for the unemployed partner, potentially raising the job finding rate ($\theta_g^l > 0$).

Dual-Searcher Households. The value function of a household where both spouses are unemployed is:

$$\begin{aligned} rU =& (1-\beta)b_m + \beta b_f \\ &+ \sum_{g\in\{m,f\}} \alpha_g^i(0) \int \{\Omega_g(w) - U\}^+ dF_g(w) + \sum_{g\in\{m,f\}} \alpha_g^o(0) \int \{\Omega_g(w) - U - \psi_h\}^+ dF_g(w) \end{aligned}$$

Worker-Searcher Households The value function of a male-headed solves:

$$\begin{aligned} r\Omega_m(w) = &(1-\beta)w + \beta b_f + \delta_m[U - \Omega_m(w)] \\ &+ \alpha_f^i(1) \int \{T(w, w_f) - \Omega_m(w), \Omega_f(w_f) - \Omega_m(w)\}^+ dF_f(w_f) \\ &+ \alpha_f^o(1) \int \{\Omega_f(w_f) - \Omega_m(w) - \psi_h\}^+ dF_f(w_f) \end{aligned}$$

A similar structure applies for female-headed households, where the wife is employed at wage w and the husband searches. The value function is:

$$\begin{aligned} r\Omega_f(w) = &(1-\beta)b_m + \beta w + \delta_f[U - \Omega_f(w_f)] \\ &+ \alpha_m^i(1) \int \{T(w_m, w) - \Omega_f(w), \Omega_m(w_m) - \Omega_f(w)\}^+ dF_m(w_m) \\ &+ \alpha_m^o(1) \int \{\Omega_m(w_m) - \Omega_f(w) - \psi_h\}^+ dF_m(w_m) \end{aligned}$$

The transitions are similar to the male-headed households. Dual-Worker Household is the same as in the baseline model

B.5.2 Estimation of the extended model

Here I present the estimates for married couples under the extended model. In addition to the 10 parameters, we now have another 4 parameters separating the offer arrival rates when spouses are employed and when they are not employed. Table A10 presents the new sets of moments used for estimation, and Table A11 presents the estimates of the 14 parameters.

There are several takeaways from the new set of estimates: First, the parameters governing arrival rates when spouses are employed are all negative, though not precisely estimated, indicating that having an employed spouse reduces the search effort of the unemployed spouse. Second, θ_m^o is close to 0 while θ_f^o is -0.665, indicating that female displaced workers with an employed spouse is even less likely to search for outside jobs. Third, with the extended model, the remaining female weight β is estimated to be larger (0.456 in the extended model versus 0.386 in the baseline model). This suggests that part of the unequal weighting of female earnings within household is reflected in the fact that women are less likely to search for jobs when their spouses are employed.

Table A10: Model-Generated Moments and Data Targets

	Married Men		Married Women	
	(1)	(2)	(3)	(4)
Moments	Model	Data	Model	Data
M1,M2. Avg unemployment duration (spouse E)	15.38	14.76	18.12	18.03
M3,M4. Avg unemployment duration (spouse U)	13.01	14.47	15.41	17.10
M5,M6. Migration share (spouse E)	0.117	0.154	0.063	0.090
M7,M8. Migration share (spouse U)	0.246	0.191	0.206	0.163
M9,M10. Average employment duration	305	306	269	269
M11,M12. Accepted wages, 10th pct	299	311	192	191
M13,M14. Mean Mover-stayer wage gap	132	55	151	35
M15. Female-to-male migration ratio	0.53	0.53		
M16. Female-to-male wage ratio	0.71	0.62		

Notes: This table presents model-implied and empirical values of the moments. Column 1-2 report the values for married men and column 3-4 for married women. The odd numbers represent the moments for married men, while the even numbers represent married women.

Table A11: Estimated Parameters - Married

Parameters	(1) Estimates	(2) s.e.	(3) Sensitivity
Panel A: Married Men			
Inside offer arrival rates (spouse U), α_m^i	0.072	0.0194	M12,M7,M3
Outside offer arrival rates (spouse U), α_m^o	0.024	0.0060	M12,M3,M7
Inside offer arrival rates (spouse E), θ_m^i	-0.106	0.1254	M3,M7,M12
Outside offer arrival rates (spouse E), θ_m^o	-0.0003	0.4349	M4,M3,M12
Job destruction rate, δ_m	0.0033	0.00003	M9,M6,M15
Value of unemployment, b_m	-3833.0	700.6	M4,M3,M12
Panel B: Married Women			
Inside offer arrival rates (spouse U), α_f^i	0.054	0.0063	M8,M7,M3
Outside offer arrival rates (spouse U), α_f^o	0.014	0.0019	M7,M8,M3
Inside offer arrival rates (spouse E), θ_f^i	-0.098	0.2877	M12,M3,M4
Outside offer arrival rates (spouse E), θ_f^o	-0.665	1.9549	M12,M3,M4
Job destruction rate, δ_f	0.0037	0.00004	M10,M6,M15
Value of unemployment, b_f	-1874.0	970.1	M3,M8,M14
Panel C: Household Level			
Migration cost, ψ	9.642	2564.1	M7,M13,M12
Female weight, β	0.456	0.0874	M8,M4,M14

Notes: s.e. denotes standard errors. Column 3 reports the three most important moments for each parameter in estimation based on the sensitivity measure of Andrews et al. (2017).

C Estimation and Validation

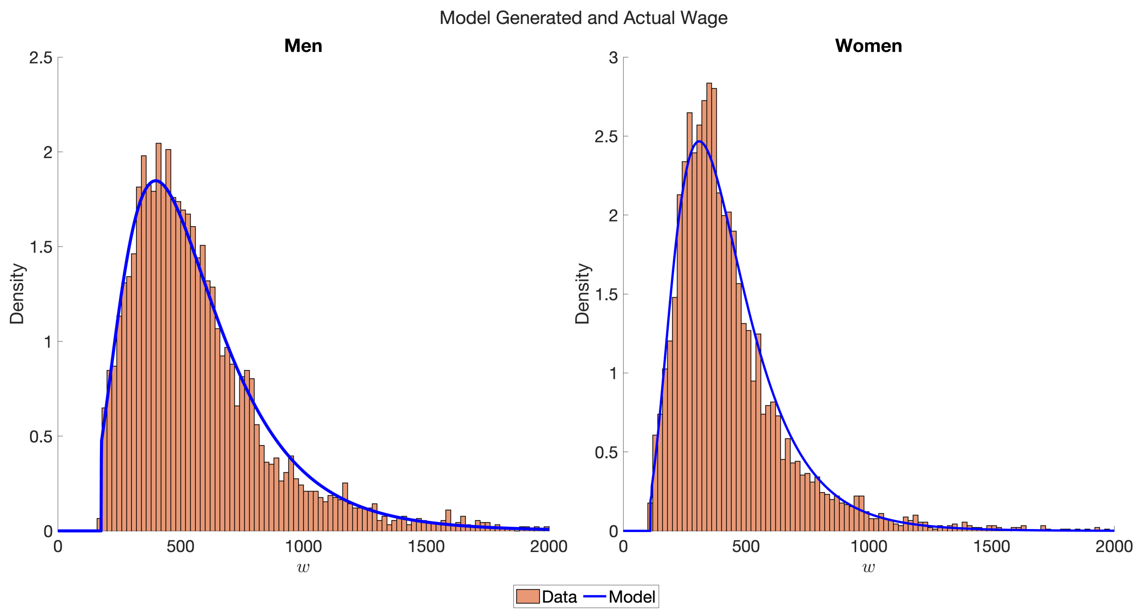
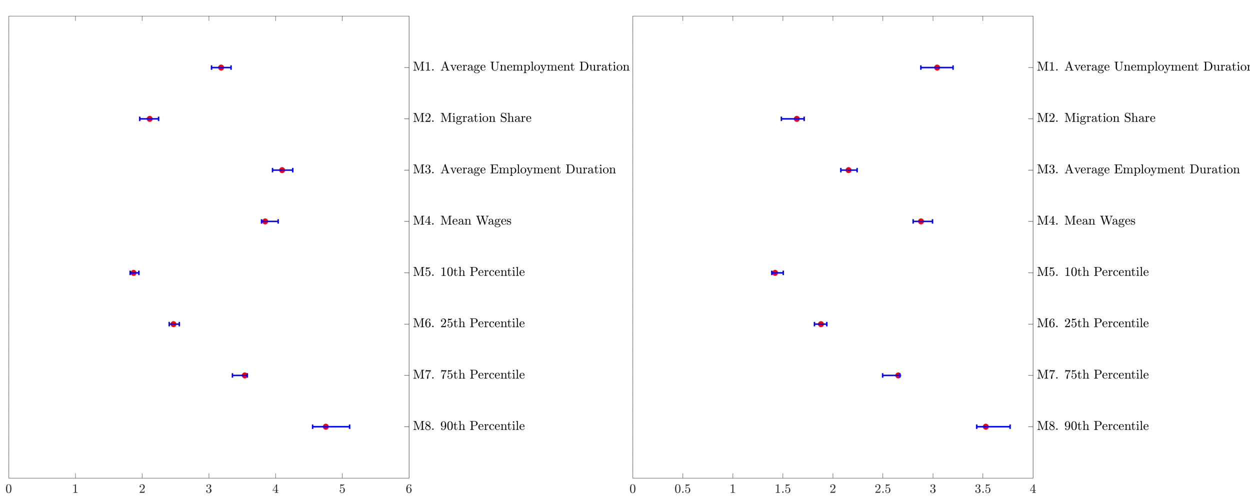


Figure A6: Steady State Wage Distribution - Single Men and Women

Notes: This figure presents model-implied steady-state wage distribution (blue line) and the empirical wage distribution (orange bars) for single men (left panel) and single women (right panel)



(a) Single Men

(b) Single Women

Figure A7: Model Fit: Model Moments with Data CI

Notes: The red dots indicate the model-implied value of each moment and the blue bars are the corresponding ranges of the empirical moment calculated from bootstrapped sample. Moments are rescaled so that they can be plotted in the same graph.