Preliminary and incomplete

Moving to Opportunity, Together*

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Abstract

Many couples face a trade-off between advancing one spouse's career or the other's. We study this trade-off by analyzing the earnings effects of relocation and the effects of a job layoff on the probability of relocating using detailed administrative data from Germany and Sweden. Using an event-study analysis of couples moving across commuting zones, we find that relocation increases men's earnings more than women's, with strikingly similar patterns in Germany and Sweden. Using a sample of mass layoff events, we find that couples in both countries are more likely to relocate in response to the man being laid off compared to the woman. We then investigate whether these gendered patterns reflect men's higher earnings or a gender norm that prioritizes men's career advancement. To do this, we develop a model of household decision-making where households place more weight on the income earned by the man compared to the woman, and we test the model using the subset of couples where the man and woman have similar potential earnings. In both countries, we show that the estimated model can accurately reproduce the reduced-form results and can also quantitatively reproduce most of the observed female "child penalty."

JEL classification: J61, J16, R23

Keywords: Labor migration, tied movers, gender gap in earnings

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1 Introduction

Over the past half a century, women's participation in the labor market has risen sharply in most OECD countries, and dual-earner couples have become the norm.[1] When each spouse contributes to household income, couples will have to make location decisions based on the potential job opportunities for each spouse. As a result, couples may face a trade-off: since job opportunities vary across regions, advancing one spouse's career may come at the expense of the other's, leading to the so-called "co-location problem" (Costa and Kahn 2000).

Early models of the household predict that couples will make location decisions to maximize joint income (Mincer 1978; Frank 1978). Joint location decisions may therefore result in a gender earnings gap if men have higher earnings or higher earnings potential than women. Couples may choose to locate in areas that benefit the man's career while the woman becomes the "trailing spouse", working in a job that does not suit her skills or has lower earnings potential than if she was maximizing only her own earnings. However, numerous studies have shown that gender norms also influence household and individual decision-making (see, for example, Bertrand et al. 2015; Bursztyn et al. 2017).

In this paper, we use administrative data from Germany and Sweden to study the impact of moving on men's and women's earnings, and to test how much of the gender earnings gap from moving is due to differences in earnings potential versus gender norms. Using an event study design, we trace the earnings trajectories of heterosexual couples who move and find that moves disproportionately benefit men. While men's earnings increase by about 11% and 5% in Germany and Sweden over the first five years following the move, women experience small changes in their earnings of 3% and -1%, respectively. These differences persist over the first 10 years following the move (men's earnings increasing by about 17% and 11% in Germany and Sweden, while women see a more modest increase of 10% and 7%).

We find that the earnings gap that emerges can be attributed to men experiencing an increase in wages, while women spend less time in the labor market, particularly in the first year following a move. We also find that the earnings gender gap following a move appears across all age groups and is most pronounced for couples in which both the man and the woman are between the ages of 20 and 29 at the time of the move.

[1] For example, in 1970, 97% of German men and 47% of women aged 25-54 were in the labor force. By 2010, men's labor force participation rate fell to 93%, while that of women increased to 81%, according to OECD statistics (https://stats.oecd.org). Also, in 2018, 65% of children aged 0-14 living in one-couple households had both parents working full-time and/or part-time in Germany, and this percentage goes up to 80% in Sweden (https://www.oecd.org/els/family/LMF_1_1_Children_in_households_employment_status.pdf).

We also study whether couples are more likely to move when the man is laid off as opposed to the woman. We use mass layoff events to generate plausibly exogenous job separations for both men and women in our sample of couples. In Germany, we find that the likelihood of moving increases following the layoff of either a man or a woman, but couples are nearly twice as likely to move when a man is laid off compared to when a woman is laid off. In Sweden, the likelihood that a couple moves doubles when the man is laid off, but does not change significantly when the woman is laid off. These results may help explain why women suffer larger earnings losses following a layoff relative to men: they are less able to take advantage of job opportunities in other localities (Illing et al. 2021).

To distinguish between different potential explanations for these reduced-form results, we consider a model of household decision-making in which households potentially place more weight on income earned by the man relative to the woman, as in Foged (2016). An intuitive prediction of the model is that in a standard unitary model of joint income maximization (net of migration costs), moves should not systematically benefit men in couples where the man and the woman have identical pre-move earnings and earnings potential. More generally, the gender gap in the effect of moves should be decreasing in the woman's share of household income and be reversed when the woman is the primary breadwinner. We find in both countries that the earnings gap that emerges following a move is indeed smaller among couples in which the woman has a higher predicted share of household income, consistent with potential earnings differences explaining some of the overall gender gap in the earnings effects of relocation. But even among couples where women have higher potential earnings, we find in both countries that men benefit more than women following a move.

With these empirical results as motivation, we then structurally estimate the model parameters separately for each country. We test (and reject) the unitary model in both countries, with larger deviations from the unitary household benchmark in Germany than in Sweden. We also show that the model can reproduce the gender differences in the effects of a job layoff on the probability of moving, even though these results were not directly targeted in the model-based estimation. Lastly, we show that the model-based estimates can quantitatively account for most of the female "child penalty" in both countries by extending an existing model of the "child penalty" (Andresen and Nix 2022) to allow households to place less weight on income earned by the woman compared to man's (and calibrating this extended model using our country-specific estimates of the "discount" parameter β).

Our reduced-form results use a relatively standard event-study framework and mass layoff events to generate plausibly exogenous job separations. For both research designs, we present visual evidence that the identifying assumptions are plausible in both countries. Our model-based estimates require stronger assumptions, however. In particular, we assume that men and women have the same job opportunities and expected returns to migration conditional on predicted income. One way this assumption could be violated is if employers discriminate against women in making job offers to candidates in different commuting zones, perhaps in anticipation of women being less likely to be able to accept offers to relocate. To address this concern, we have replicated our heterogeneity analysis by female share of predicted income using different prediction models that allow for gender discrimination, and we find broadly similar results.

Overall, we conclude that our empirical results and model-based estimates suggest that a gender norm that prioritizes men's career advancement can simultaneously (and parsimoniously) account for three distinct gender differences in labor market outcomes: the earnings effects of relocation, the probability of moving following a job layoff, and the earnings effects of the birth of a child.

Our paper relates to a large literature on the source of gender gaps in labor market outcomes. A number of papers have found that child penalties play an important role in the remaining gender gap (Angelov et al. 2016; Cortes and Pan 2022; Kleven et al. 2019a,b). Women, who typically take over more care responsibilities than men, have disadvantages when long working hours or working particular hours is rewarded (Bolotnyy and Emanuel 2022; Goldin 2014). Women also show a lower willingness to commute (Le Barbanchon et al. 2020). In addition, social norms or psychological attributes such as being willing to compete, risk preferences, and self-confidence may directly affect job search and wages (e.g. Bertrand et al. 2015; Buser et al. 2014; Cortes et al. 2021; Wiswall and Zafar 2017). A further potential explanation, which is the focus of this paper, is that married women may take less advantage of career enhancing long-distance moves or may even experience earnings losses as a tied mover.

In this space, a number of papers have examined joint location decisions and the rise of female labor force participation. Early papers, such as Mincer (1978), model household decision-making under the constraint that, within a couple, one individual is typically "tied". That is, the individual benefits less from migration made under household decisions than if they could move individually. These early papers document women's increased labor force participation as a constraint on individual optimization, but do not directly test how migration decisions are made. A number of papers have since empirically documented couples' location decisions, noting that married couples are less likely to move than single individuals, and also move to different areas (Costa and Kahn 2000; Compton and Pollak 2007; Rabe 2009; Blackburn 2010a). Studies that attempt to directly study the impact of moving on gender inequality have typically had to use a selected sample or are unable to establish causality. For example, Burke and Miller (2018) use military spouses to estimate the impact of an exogenous move on the spouse's labor market outcomes, and Nivalainen (2004) looks at families in Finland and shows that most moves occur to help the man's career. By using administrative data from Sweden and Germany and an event study design, we contribute to this literature by estimating the causal impact of couples moving on men's and women's earnings covering a large and fairly representative sample of heterosexual couples in the entire working-age population.

Our paper also relates to more recent research examining the implications of location decisions on gender inequality. Fadlon et al. (2022) examine how early labor market choices impact career and family outcomes for male and female physicians in Denmark. Exploiting the lottery system that allocates physicians to initial internships, the authors find that the geographic location of the internship explains a large fraction of gender inequality in human capital accumulation and wages, suggesting that women may be more tied to location. Venator (2020) uses the NLSY97 to test how unemployment insurance generosity affects couples' migration decisions, finding that access to UI increases migration rates as well as women's post-move earnings. Relative to this work, we develop and test an alternative model-based explanation that allows for a gender norm that prioritizes the man's career within the couple.

The remainder of the paper proceeds as follows. We describe the two administrative datasets as well as our sample and variable construction in section 2. Section 3 describes our empirical strategy and results are presented in section 4. Section 5 develops a model of household decision-making and presents additional empirical results motivated by the model. Section 6 concludes.

2 Data

We use administrative data from Sweden and Germany to test whether moves disproportionately benefit men in heterosexual couples. These datasets are ideal for three reasons. First, in each dataset, we have geographic information on the place of residence for each spouse that is necessary to investigate the effects of joint moves. Second, the data include detailed labor market histories of both spouses, allowing us to precisely account for spouses' pre-move employment outcomes and study the post-move dynamics. Third, we can identify mass layoff events at the establishment level, using them as an exogenous negative labor market shock that could lead to a move.

2.1 German Data

For Germany, we use a 25% random sample of married couples that can be identified in the administrative data base Integrated Employment Biographies (IEB).[2] The IEB includes all employees subject to social security (this excludes civil servants and self-employed), all people who receive unemployment benefits, and those who have been registered as searching for a job. Married couples are identified according to the method of Goldschmidt et al. (2017): for two people to be matched as a couple, the spouses have to live at the same location, have a matching last name, be of different sexes, and have an age difference of less than 15 years.[3] The identification of couples is done every year on June 30 which implies that our data only includes couples of whom both spouses have a record in the IEB for that particular date. It also means that we cannot be sure whether two individuals remain a couple in cases in which at least one of the two individuals does not have a data record on June 30th in the following years.

The dataset consists of day-to-day information on every period in employment covered by social security, every period of receiving unemployment insurance benefits, as well as information on periods of job search and participation in subsidized employment and training measures. For each period, it contains information on the corresponding wages and benefit levels. The wage information is accurate, as the employer has to report wages for social security purposes. In addition, the data include a rich set of personal characteristics such as occupation, nationality, year of birth, education, and job requirement level. For each employee, we also observe information on the employers, such as firm size, average wage at the firm and industry, obtained from the Establishment History Panel (BHP)[4]. In our analysis, we use this link between employees and firms to identify mass layoffs.

2.2 Swedish Data

We use individual-level administrative data from Sweden from the GEO-Sweden database. The database covers the entire Swedish population of 10 million people, whom we can track over time starting in 1990. In addition, we can identify the building in which individuals reside, allowing us to identify couples. Specifically, we identify heterosexual couples as individuals of the opposite sex who move to and from the same building in the same year. We restrict the data in several ways to construct our final sample of couples, described in detail in sub-section 2.4.

[2] The data product we use is produced by the Institute of Employment Research (IAB). The data are processed and kept by the IAB according to Social Code III. The data contain sensitive information and are therefore subject to the confidentiality regulations of the German Social Code (Book I, Section 35, Paragraph 1). The data are held by the IAB, Regensburger St 104, D-490478 Nuremberg, email: iabiab.de, phone: +49/911 1790. If you wish to access the data for replication purposes, please get in contact with the authors and the IAB.

[3] This identification method increases the likelihood of identifying certain types of couples: 1) older couples, 2) more conservative couples, and 3) couples living in smaller buildings (Goldschmidt et al. 2017).

[4] Throughout this paper, we use the term firm for simplicity. Note that we can only identify establishments and are unable to link them to firms.

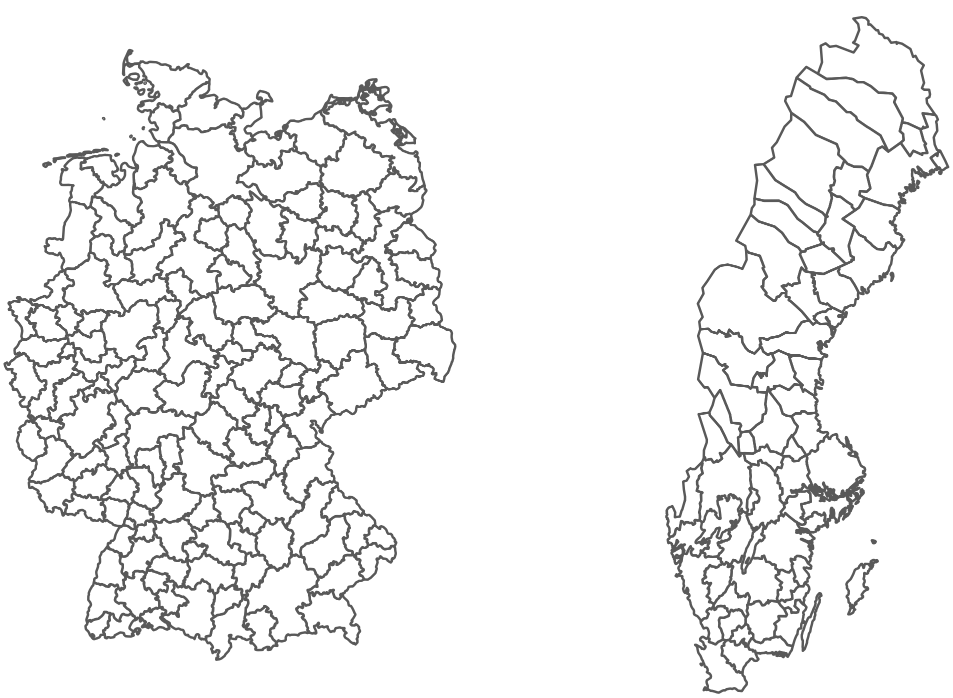
2.3 Moving Across Commuting Zones

To focus on couples that change local labor markets when they relocate, we study moves across commmuting zones using district-level information on each couple's place of residence. Kosfeld and Werner (2012) define commuting zones in Germany as districts connected through high commuter flows and identify 141 commuting zones in Germany. For Sweden, we use Statistics Sweden's concept of *FA-regioner* to identify 60 commuting zones[5], see Figure 1.

In the German data, the information on the place of residence is only determined at the end of each year for most spells[6]. We therefore allow for the possibility that one spouse moves in year t while the other follows in year $t + 1$.

Figure 1: Maps of Commuting Zones

(a) Germany (b) Sweden



Notes: This figure displays the maps of the commuting zones in Germany and Sweden. Commuting zones in Germany follow Kosfeld and Werner (2012).

[5] More details here https://www.scb.se/contentassets/1e02934987424259b730c5e9a82f7e74/fa_karta.pdf.

[6] For employment spells (BeH), which form the bulk of observations, the information on the place of residence is determined at the end of each year. For job seeker spells (ASU), unemployment benefit spells (LeH), and participant in training measures spells (MTH and XMTH), the information on the place of residence applies to the beginning of the original period. Only for unemployment benefit 2 recipient spells (LHG) and XASU spells (ASU spells reported by municipal institutions) the information applies to the entire period of original observation.

2.4 Sample Selection, Variable Definition, and Descriptive Statistics

2.4.1 Movers Sample

In our analysis, we consider all joint moves of couples occurring between 2002-2007 Sweden and 2001-2011 in Germany. During the observation period, a few couples experienced multiple long-distance moves. We consider only their first move, because future outcomes may be influenced by the first move. We therefore abstract from repeated migration.

We exclude couples where neither spouse is 25 to 45 years old at the time of the move, as well as couples with an age difference larger than 15 years.[7] In the Swedish data, we use the receipt of student benefits to identify and exclude couples in which at least one person is a student in the five years preceding a move. In the German data, we are excluding couples in which at least one person is in education (e.g. apprentice, intern) in the five years before a move.[8] Finally, couple-years in which one spouse is above 60 or below 16 years old are excluded.

We construct a panel that includes all couples that we observe at least 2 years before the move to 4 years thereafter (i.e., a partially balanced panel). Our final sample consists of $12,747$ moving couples in Germany and $44,499$ couples in Sweden.

2.4.2 Variable Definitions and Descriptive Statistics

The main outcome variable that we consider in our analysis is gross yearly wage income (in 2017 euros) of each spouse. For non-working spouses, the wage income is zero. Changes in wage income may therefore be either due to changes at the extensive or intensive margin.

Table 1 presents descriptive statistics for our two samples. The average age of couples in similar in each sample. Education levels are different, in large part due to differences in the education systems. Sweden has a lower part-time employment rate for women. For the age group from 25 to 54 years old, in 2010, the share of part-time workers for men and women were 5.6 and 39.1% in Germany, and 5.0 and 13.4% in Sweden[9]. Table 2 presents descriptive statistics for the layoffs sample (with some missing values for Sweden, for now).

[7] We do this to ensure that we do not accidentally pick up on child-parent pairs.

[8] We exclude students so that any income changes following a move are not due to initial entry into the labor market.

[9] These statistics are from OECD's indicator of share of employed in part-time employment, by sex and age group (`https://stats.oecd.org/`). If we consider the Swedish definition of part-time employment –less than 35 hours a week, as opposed to OECD's definition of less than 30 hours–, we find a part-time employment rate of about 30% for Sweden in their own statistics (`https://pxweb.nordicstatistics.org`).

Table 1: Summary Statistics for Movers Sample

	Germany		Sweden	
	Men (1)	Women (2)	Men (3)	Women (4)
Age	36.16	33.87	35.00	32.71
	(6.17)	(6.12)	(6.86)	(6.33)
Compulsory schooling	0.01	0.03	0.13	0.12
	(0.11)	(0.17)	(0.33)	(0.33)
High school	0.05	0.06	0.48	0.44
	(0.21)	(0.25)	(0.50)	(0.50)
Vocational training	0.60	0.68	0.07	0.04
	(0.49)	(0.46)	(0.26)	(0.20)
Some college	0.34	0.22	0.57	0.56
	(0.47)	(0.42)	(0.50)	(0.50)
Potential experience	17.17	15.17	15.32	13.03
	(6.43)	(6.32)	(0.43)	(0.45)
Wage income (1000s EUR)	44.11	19.79	28.94	16.60
	(39.95)	(22.04)	(19.48)	(14.05)
Employed	0.88	0.78	0.89	0.84
	(0.33)	(0.41)	(0.31)	(0.36)
Unemp. benefits (1000s EUR)	0.61	0.39	0.90	0.99
	(2.06)	(1.40)	(2.72)	(2.59)
Days receiving UI benefits (per year)	20.80	20.92	23.94	24.51
	(66.30)	(70.20)	(64.71)	(62.95)
At least 1 child	0.38	0.38	0.66	0.66
	(0.49)	(0.49)	(0.47)	(0.47)
Non-native	0.08	0.08	0.13	0.14
	(0.27)	(0.28)	(0.34)	(0.35)
Observations	12747	12747	44499	44499

Notes: This table displays means and standard deviations (in parentheses) for different outcomes in the period before the move ($t-1$) in Germany and Sweden for the movers sample.

Table 2: Summary Statistics for Job Layoffs Sample

	Germany				Sweden			
	Layoff Men		Layoff Women		Layoff Men		Layoff Women	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
Age	38.26	36.51	40.77	38.24	36.49	34.89	39.02	36.41
	(4.85)	(5.65)	(5.93)	(5.03)	(4.95)	(5.63)	(6.21)	(5.06)
Compulsory schooling	0.01	0.02	0.01	0.01	.	.	.	.
	(0.09)	(0.15)	(0.08)	(0.10)	.	.	.	.
High school	0.09	0.09	0.06	0.09	.	.	.	.
	(0.28)	(0.28)	(0.23)	(0.29)	.	.	.	.
Vocational training	0.76	0.79	0.78	0.79	.	.	.	.
	(0.43)	(0.41)	(0.41)	(0.41)	.	.	.	.
Some college	0.14	0.10	0.15	0.11	.	.	.	.
	(0.35)	(0.30)	(0.36)	(0.31)	.	.	.	.
Potential experience	19.76	18.07	22.03	19.69	17.08	15.49	19.86	17.13
	(5.07)	(5.85)	(6.13)	(5.29)	(5.32)	(5.88)	(6.73)	(5.53)
Wage income (1000s EUR)	43.87	16.95	41.14	28.17	38.21	17.39	32.71	25.43
	(27.14)	(17.11)	(30.97)	(15.63)	(16.08)	(13.47)	(19.12)	(12.16)
Employed	1.00	0.85	0.93	1.00	1.00	0.90	0.93	1.00
	(0.00)	(0.36)	(0.25)	(0.00)	(0.00)	(0.30)	(0.25)	(0.00)
Unemp. benefits (1000s EUR)	0.60	0.30	0.43	0.45	.	.	.	.
	(1.61)	(1.19)	(1.70)	(1.21)	.	.	.	.
Days receiving UI benefits (per year)	16.47	18.60	16.16	18.77	.	.	.	.
	(41.26)	(70.34)	(59.97)	(46.28)	.	.	.	.
At least 1 child	0.57	0.57	0.47	0.47	.	.	.	.
	(0.49)	(0.49)	(0.50)	(0.50)	.	.	.	.
Non-native	0.08	0.07	0.05	0.05	0.10	0.11	0.10	0.09
	(0.28)	(0.26)	(0.23)	(0.22)	(0.30)	(0.31)	(0.30)	(0.29)
Observations	6828	6828	4458	4458	7986	7986	6732	6732

Notes: This table displays means and standard deviations (in parentheses) for different outcomes in the period before the layoff ($t-1$) in Germany and Sweden for the job layoffs sample.

3 Empirical Strategy

We follow an event study approach to estimate the impact of a move on men's and women's labor market outcomes. The usual identification assumptions for event an event study design are no-anticipation and parallel trends. This involves that the event (moving) is not determined by the outcome (earnings or employment). In our setting, it is likely that individuals choose to move in response to income or employment shocks. However, we are particularly interested in whether couples are equally likely to move in response to a shock to a man's or a woman's career. The biggest threat to our strategy is that couples move when women (or men) are choosing to exit or enter the labor market, or to work less. For example, if couples choose to move when they are starting a family, the move will coincide with women temporarily leaving the labor market. We therefore control for an individual's potential experience and education level, as well as calendar year and child event-time indicators. These controls, and the fact that we exclude students, should account for potentially endogenous reasons why couples might move.

Our main estimation equation is

$$
\begin{aligned}
Y^g_{ist} = \sum_{j\neq -1} \alpha^g_j \times \mathbb{1}[j = t] + \sum_k \beta^g_k \times \mathbb{1}[k = \hat{\text{exp}} + \sum_p \gamma^g_p \times \mathbb{1}[p = \text{educ}_{is}] \\
+ \sum_y \nu^g_y \times \mathbb{1}[y = s] + \sum_m \tau^g_m \times \mathbb{1}[m = t_{ch}] + \theta^p_n \times \mathbb{X} + \epsilon^g_{ist} \qquad (1)
\end{aligned}
$$

where the outcome of interest is individual i's wage income in year s and event time t. The first term consists of event-time indicators, which we estimate for five years before and ten years after a move. We estimate equation 1 separately by gender g and include controls for potential experience ($e\hat{x}p$), education level ($educ$), calendar year ($y = s$), and child event-time ($m = t_{ch}$).[10] Standard errors are clustered at the individual level.

[10]There are five education levels: compulsory schooling, high school, vocational training, some college, and college.

4 Results

4.1 Descriptive Results

We begin by separately plotting men's and women's unconditional wage income and employment status following a move, shown in Figure 2. Panels (a) and (b) show the wage income for German and Swedish couples who move together for the first time. Both men's and women's incomes are relatively flat prior to the move in time 0, after which men's income steadily increases. For both countries, we see a slight dip in women's earnings around the time of a move followed by steady income growth.

These moves partly appear to occur following a period of unemployment. Panel (c) and (d) show that men and women receive fewer days of unemployment benefits following a move, although there is a spike in benefit collection for women in the year and or the year after a move. These results provide initial evidence that these moves may be for the benefit of men's careers.

4.2 Main Results: Earnings Effects of Moving Across Commuting Zones

We now turn to our main estimation strategy, in which we compare the labor market outcomes for men and women who move while controlling for experience, education, calendar year, and child event-time indicators. We plot the coefficients from estimating equation 1 in Figure 3. The coefficients are plotted relative to the average of the outcome variable in the year before the move ($t-1$).

In both Germany and Sweden, a gap between men's and women's earnings emerges the year of the move and steadily grows over time. Five years after a move, men are earning about €8,000 and €3,000 more than they were in the year prior to the move, while women are earning about €2,000 and €1,000 more in Germany and Sweden respectively.

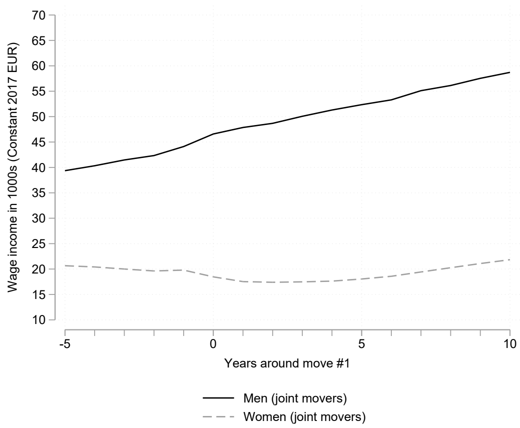
To investigate whether spouses' earnings responses are driven by changes in employment or in wages, panels (c) and (d) of Figure 3 and (a)-(f) of Figure OA-2 show the effects of a move on various employment measures of men and women. In Germany, the number of days a person is employed increases by 20 days per year in the year immediately following a move for men and by less than 10 days per years for women. However, employed days continue to increase over time and eventually converge. We also see a spike in the number of days an individual collects unemployment benefits in year following a move that is much more pronounced for women than for men (17 days versus 7 days). These results suggest that at least part of the divergence in men's and women's earnings is due to women leaving employment for a period of time following a move.

The results in Figure 3 indicate that relocation increases wage earnings of men more than women in absolute terms, and Figure 4 indicates that this is true in proportional terms, as well. Figure 4 normalizes the event study estimates in Figure 3 (panels (a) and (b)) by the average income of men and women in each country in the year prior to the move).[11] These results show that moving increases the average earnings growth for men by a greater percentage than women; specifically, 10 years after the move, men experience a 9.6 percentage point higher earnings growth compared to women in Germany, and in Sweden the gender gap is 4.3 percentage points. Interestingly, in both countries men and women experience long-run increases in earnings, but men experience greater earnings growth in both absolute and percentage terms. The fact that average earnings increase significantly for both members of the household is consistent with non-negligible migration costs.

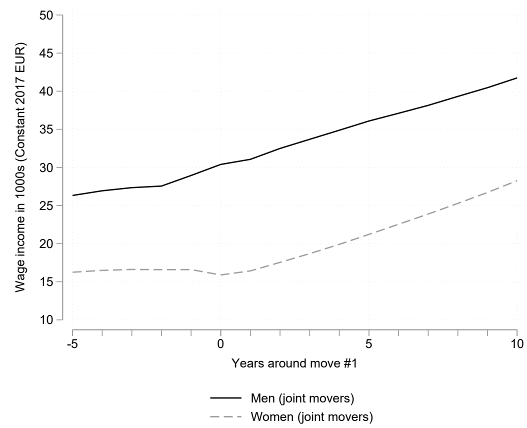
[11] This normalization follows the approach in the recent "child penalty" literature (see, e.g., Kleven et al. 2019a).

Figure 2: Relationship between Moving and Labor Earnings and Employment

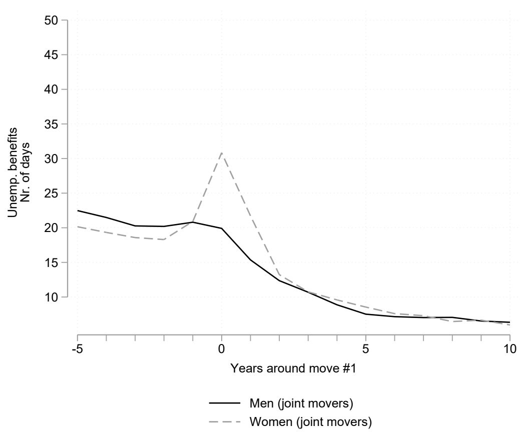
(a) Wage Income, Germany



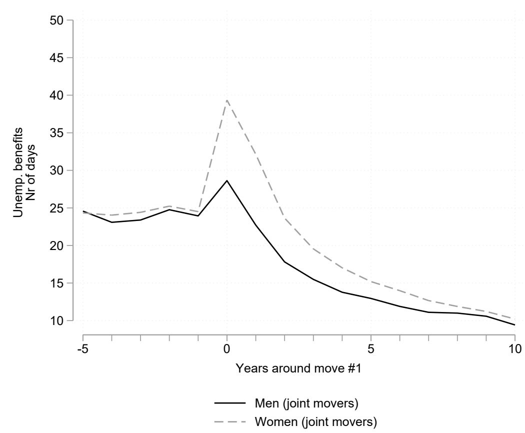
(b) Wage Income, Sweden



(c) Days Unemployment Benefits, Germany



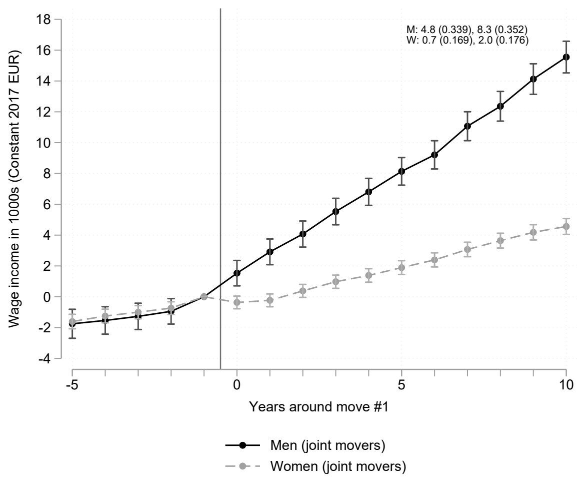
(d) Days Unemployment Benefits, Sweden



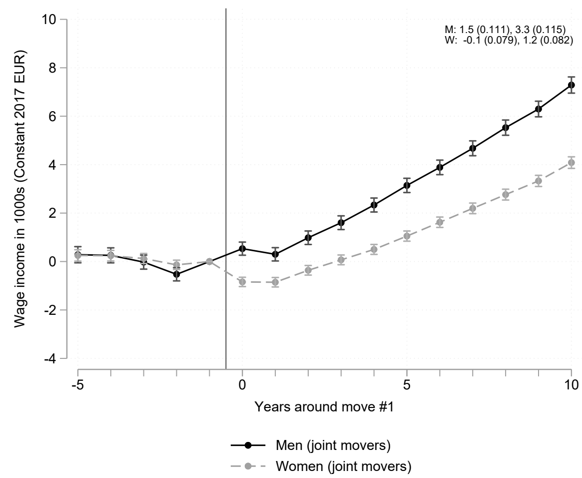
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first move, per gender.

Figure 3: Impact of Move on Labor Earnings and Employment

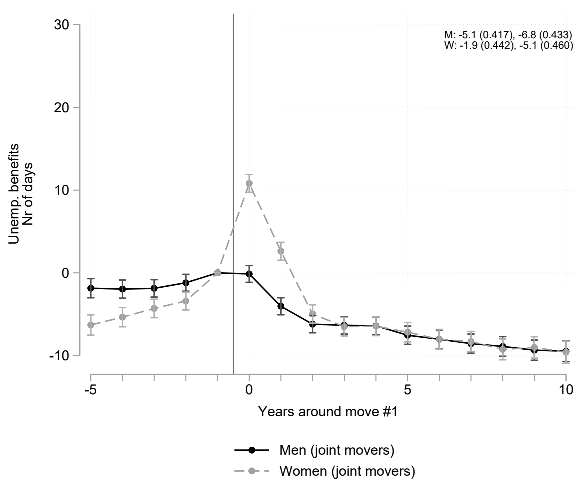
(a) Wage Income, Germany



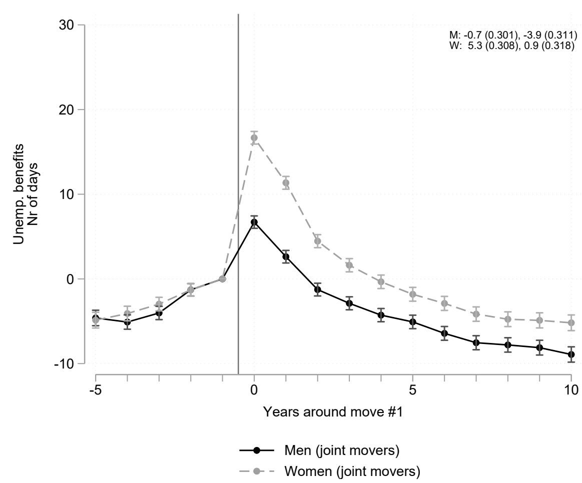
(b) Wage Income, Sweden



(c) Days Unemployment Benefits, Germany

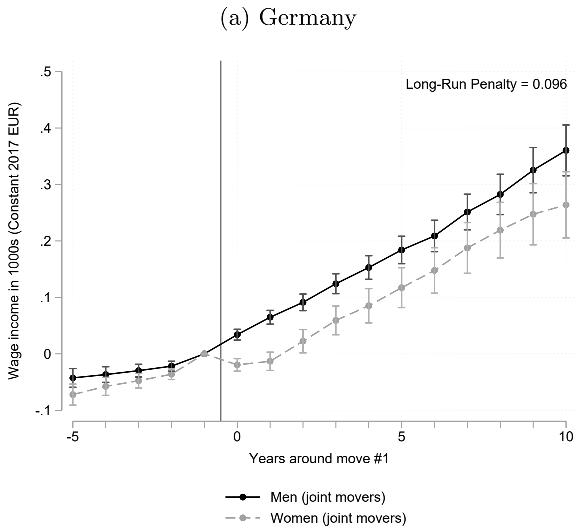


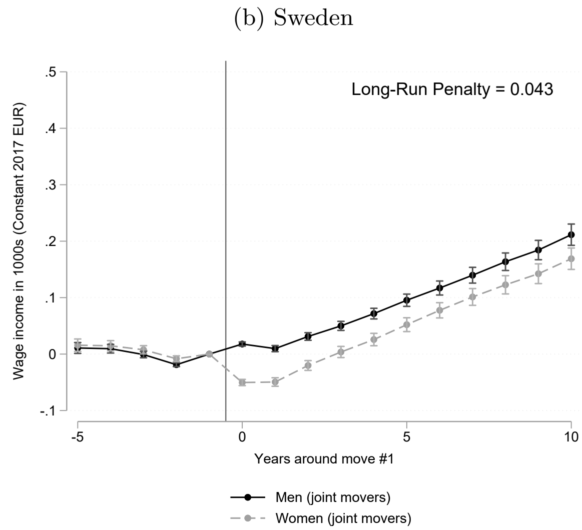
(d) Days Unemployment Benefits, Sweden



Notes: This figure displays the event study results that estimate the effect of moving on different outcomes in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W).

Figure 4: Proportional Impact of Move on Wage Income





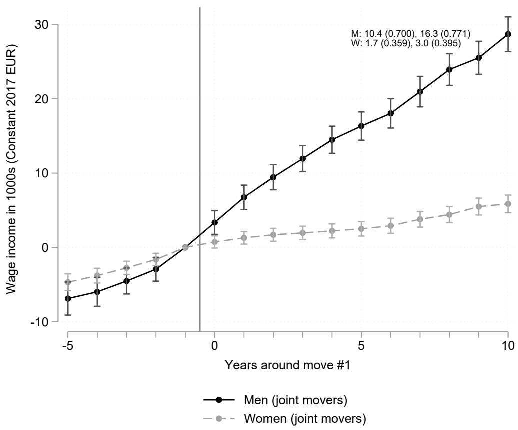
Notes: This figure displays the event study results that estimate the proportional effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The long-run penalty is calculated as in Kleven et al. (2019a) and it measures the percentage by which women are falling behind men due to move at event time $t = 10$.

4.3 Heterogeneity

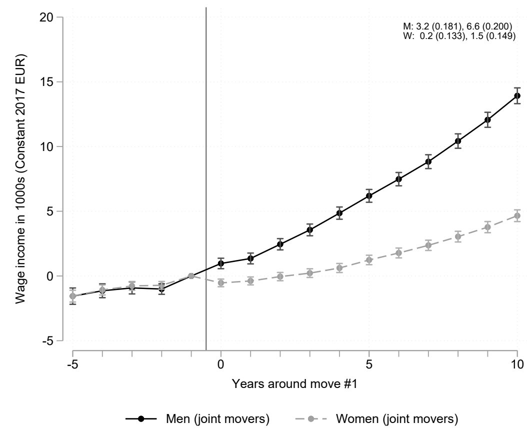
Previous research showed that young individuals are more likely to move (Polachek and Horvath 2012) and that the returns to moving are larger for younger individuals (Bartel 1979). To test whether the treatment effects vary with respect to spouses' age, we define age groups based on the average of the spouses (in pre-move year $t-1$). We define age groups for the following age intervals: $20-29$, $30-39$, and $40-50$. The results, displayed in Figure 5, show that the returns to moving decline with increasing age. For both spouses, the average treatment effects on wage income are the largest for younger couples and the lowest for older couples. We see gender differences in the returns to moving for all age groups, but they are smallest among the oldest age group, where men's returns are relatively low.

Figure 5: Impact of Move on Wage Income – By Age Groups

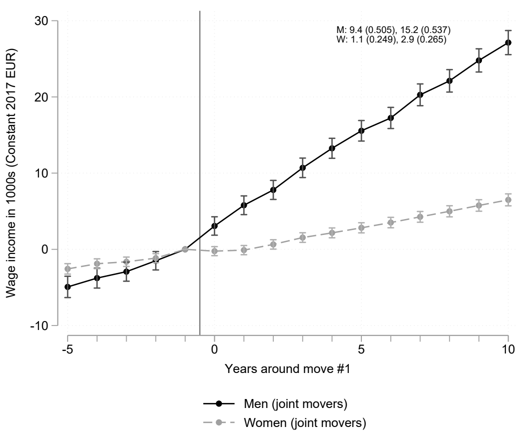
(a) 20-29, Germany



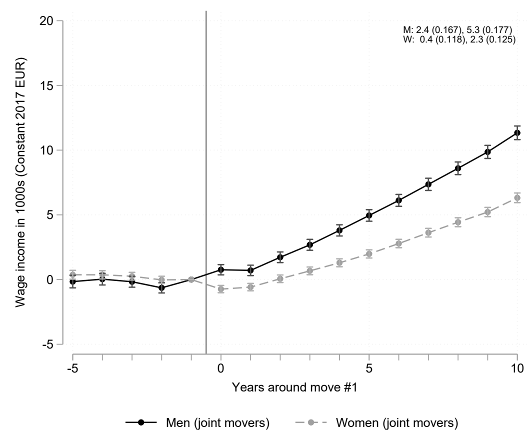
(b) 20-29, Sweden



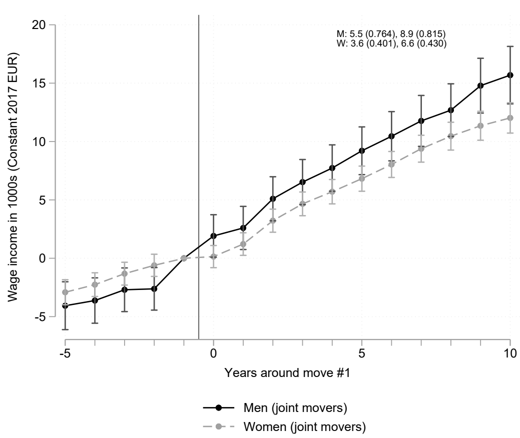
(c) 30-39, Germany



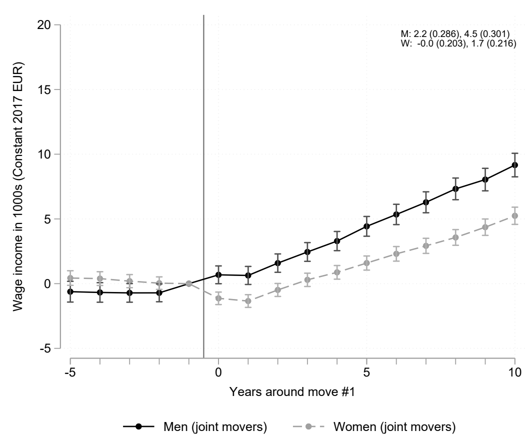
(d) 30-39, Sweden



(e) 40-49, Germany



(f) 40-49, Sweden



Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$) for different age groups. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W).

4.4 Mass Layoff Results

The previous results show the emergence of a significant earnings gap following a joint move, with men seeing more earnings growth following a move than women. In this section, we use mass layoff events to test whether couples are equally likely to move for men's and women's careers following a layoff.

We restrict our sample to the set of couples in which one person in the couple loses his or her job as part of a mass layoff. We define a mass layoff as a reduction in a firm's workforce by more than 30%. We exclude workplaces with fewer than 50 employees, as well as firms where 30% or more of employees jointly move to another workplace.[12] For the sample of mass layoff movers, the same age and student restrictions are imposed as described in section 2. In addition, we restrict the sample to individuals who have earnings of at least €8,000 in the year before the mass layoff occurs. We further focus on individuals who have worked at the firm at which they are laid off for at least one year, to minimize the possibility that we are picking up on temporary workers. We again consider an individual's first layoff.

We show descriptively how men's and women's earnings and employment change following a mass layoff in Figure OA-8. For both men and women, wage income drops sharply the period of the mass layoff ($t = 0$). Men's income appears to recover to it's $t = -1$ level about five years after the layoff whereas for women the recovery is slower (panels a and b).

In Table 3 we examine how the likelihood of moving depends on whether a man or a woman within a couple is laid off. We regress an indicator that takes the value one if a couple moves in the year of a mass layoff (or the year after) on indicators for either the man or the woman being laid off. Column 1 shows that the likelihood of moving increases by 1.5 percentage points when a man is laid off (relative to a baseline moving rate of 1.1%) and by 0.7 percentage points when a woman is laid off. These estimates do not change when we include age and commuting zone fixed effects (columns 2 and 3).

[12] We assume that in this case, the firm has been acquired or has split of part of its operations.

Table 3: Impact of Layoffs on Moving Probability

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Layoff Men	0.00680***	0.00581***	0.00594***	0.0138***	0.0141***	0.0136***
	(0.00147)	(0.00149)	(0.00148)	(0.00190)	(0.00190)	(0.00189)
Layoff Women	0.00127	0.00149	0.00174	-0.00420***	-0.00145	-0.00184
	(0.00143)	(0.00143)	(0.00144)	(0.00130)	(0.00131)	(0.00131)
Age FE		✓	✓		✓	✓
CZ FE			✓			✓
# Layoff Men	6828	6828	6828	7986	7986	7986
# Layoff Women	4458	4458	4458	6731	6731	6731
Mean	0.00719	0.00719	0.00719	0.0153	0.0153	0.0153
P-Value	0.041	0.191	0.146	<0.001	<0.001	<0.001
Observations	165449	165449	165449	280959	280959	280959

Notes: This table displays point estimates and standard errors clustered at the individual level (in parentheses) for the impact of layoffs for men and women on the probability of moving in t or $t+1$. The p-values refer to the test of whether the men and women layoff coefficients are equal. These regressions are run on the full sample of couples
* $p < .1$, ** $p < .05$, *** $p < .01$

5 Model-Based Estimation

The results in the previous sections show that in both Germany and Sweden, men's earnings increase more than women's when couples move across commuting zones. Additionally, we find that job layoffs increase the probability that a household moves across commuting zones by a greater degree when the man in the couple is laid off compared to the woman. There are numerous potential explanations for these results, but we focus on distinguishing between two of them: (1) men's higher potential earnings and greater returns to migration compared to women, and (2) a gender norm that prioritizes men's career advancement.

To distinguish between these two explanations, we develop a model of the household migration decision that extends the standard unitary household model by allowing the household to potentially place more weight on income earned by the man relative to the woman (Foged 2016). We use the model to derive additional new empirical tests for whether or not the results in the previous sections can be rationalized with a standard unitary model with gender differences in potential earnings[13].

After presenting our theoretical results, we report additional empirical results that are directly motivated by the model, and we estimate the model parameters – separately for each country – using these additional empirical results and other moments from the data. We then use the model parameters to test (and reject) the unitary model in both countries, finding larger deviations in Germany as compared to Sweden. Lastly, we use the estimated model parameters to simulate the effects of job layoffs on migration (to compare to the estimated effects of job layoffs documented above), as well as the earnings effects of childbirth (the so-called "child penalty").

5.1 Model

Model setup. There is a unit mass of households, each household has a male ($i = M$) and a female ($i = F$), and there are two periods ($t = 1, 2$). Households decide whether or not to move between the two periods. Income in period 1 represents each individual's pre-move permanent income and is assumed to be drawn independently from a log-normal income distribution: $\log(y_{i1}) \sim N(\mu_i, \sigma^2)$.[14] With this setup, there is an average gender gap in period 1 of $\exp(\mu_M + \sigma^2/2) - \exp(\mu_F + \sigma^2/2)$. Define $s = y_{F1}/(y_{M1} + y_{F1})$ to be the female's share of total household income in period 1.

Migration decision. For simplicity, we assume that each household member receives the same income in period 2 if the household chooses not to move. Each household member independently draws a potential income in period 2 that they would receive if they move, with $y_{i2} = (1 + \varepsilon_{i2})y_{i1}$ and $\varepsilon_{i2} \sim N(\mu_r, \sigma_r^2)$. The μ_r and σ_r parameters capture heterogeneity in the returns to migration, and we assume that the average return to moving is the same across genders when expressed as a percentage of baseline income.

[13]Like our model, Foged (2016) develops a model where households discount income earned by the wife relative to the husband, but the paper focuses on developing predictions about how the probability of moving varies with the female earnings share of household income, while we focus on how the expected change in income after moving varies with the female earnings share. As we show in the Appendix using simulations, the predictions in Foged (2016) on how the probability of moving varies with the female earnings share is sensitive to functional form assumptions and is not robust to extensions for assortative mating, while our simulations show that our predictions in Propositions 1 and 2 are robust to both of these extensions. As a result, we conclude that the earnings effects of migration are a more robust and reliable way to infer whether or not households discount income earned by the wife relative to the husband.

[14]This baseline setup implicitly assumes no assortative mating and assumes that the log income distributions for men and women have equal variances. We relax both of these assumptions in the Online Appendix and show in simulations that our main propositions go through with both of these extensions.

We assume that a **unitary household** chooses to move if and only if the increase in household income from moving is greater than the household's (money-metric) utility cost of moving c. Define the change in income for each household member as $\Delta y_i = y_{i2} - y_{i1}$. With this setup, a unitary household moves if $\Delta y_M + \Delta y_F > c$. A **non-unitary household** places relatively less weight on the female's income by a share parameter β (with $0 < \beta < 1$); this type of household will move if $\Delta y_M + \beta \Delta y_F > c$.

The following proposition describes the expected return to moving (conditional on moving) in the full population:

Proposition 1 *If $\mu_M > \mu_F$ and all households are unitary households, then the expected return to moving (conditional on moving) is larger for men than women: $E[\Delta y_M - \Delta y_F | \Delta y_M + \Delta y_F > c] > 0$.*

Proof. *See Appendix.*

This proposition shows that if there is a baseline gender gap and the returns to migration are (assumed to be) the same for both genders, then this implies that in unitary households men will systematically benefit from moving relative to women.

Intuitively, it is more likely that the male household member draws a potential income in period 2 that exceeds the household's cost of moving, and so conditional on moving, it is more likely that the move is a move that benefits the man rather than the woman. This implies that the previous reduced-form empirical results on their own do not reject a standard unitary model and do not necessarily imply any inefficiency in household decision-making.

The full proof is given in the Appendix, but some intuition can be gained from the following lemma:

Lemma 1 *If $\mu_M > \mu_F$ and all households are unitary households, then the expected return to moving (conditional on moving) is larger for men than women for any household with $0 < s < 0.5$; i.e., for all $0 < s < 0.5$, $E[\Delta y_M - \Delta y_F | s, \Delta y_M + \Delta y_F > c] > 0$.*

Proof. *See Appendix.*

Lemma 1 says that for any household with $0 < s < 0.5$, the expected return to moving is larger for men than women. Since $\mu_M > \mu_F$ and there is no assortative mating in our baseline model, then $E[s] < 0.5$ in the population. As a result, integrating across all households in the population ends up with an unconditional average return that is larger for men than women.

While Proposition 1 shows that it is not possible to rule out a unitary model based on the gender gap in expected returns to migration (among the households who choose to move), the next proposition shows that for the households at $s = 0.5$, the expected return to moving (conditional on moving) is the same for men and women:

Proposition 2 *If* $\mu_M > \mu_F$ *and all households are unitary households, then the expected return to moving (conditional on moving) for men and women is equal for households at* $s = 0.5$*; i.e.,* $E[\Delta y_M - \Delta y_F | s = 0.5, \Delta y_M + \Delta y_F > c] = 0$*.*

Proof. *See Appendix.*

Proposition 2 shows that our model with unitary households makes a sharp prediction for households at $s = 0.5$. For these households, when two spouses have identical income in period 1 and the same distribution of potential returns to moving, the result is that it is equally likely that each member ends up being the "trailing spouse" when the household chooses to move. Intuitively, for the couples with $s = 0.5$, the probability of drawing a potential income that exceeds the household's mobility cost is the same for each household member. It is therefore equally likely that a move benefits the man as it benefits the woman.

Propositions 1 and 2 are both established in a very simplified setting, with baseline log income distributions for men and women having equal variance (homoskedasticity), and no assortative mating. The Appendix presents proofs and simulations of extended versions of the baseline model that allow for unequal variances across genders in baseline log income and also allow for assortative mating, and both results carry through with these model extensions.

We now turn to non-unitary households, where households behave "as if" they put less weight on income earned by the woman relative to income earned by the man, and this relative weight is given by the parameter β, with $0 < \beta < 1$ (so that $\beta = 1$ corresponds to a standard unitary household). In contrast to Proposition 2, when households are non-unitary households with $0 < \beta < 1$, the expected return to moving (conditional on moving) is larger for men compared to women at $s = 0.5$, with the gap decreasing as β approaches 1.

Proposition 3 *If* $\mu_M > \mu_F$ *and all households are non-unitary households with* $0 < \beta < 1$*, then the expected return to moving (conditional on moving) is larger for men than women for households at* $s = 0.5$*; i.e.,* $E[\Delta y_M - \Delta y_F | s = 0.5, \Delta y_M + \beta \Delta y_F > c] > 0$*, with the expectation approaching 0 as* β *approaches 1 from below.*

Proof. *See Appendix.*

Proposition 3 shows that an empirical implication of the unitary household model is that we should be able to find households with similar income and potential returns from moving, and these households should on average have returns to moving (conditional on moving) that are similar by gender. If we continue to find (within the set of households at $s = 0.5$) that men disproportionately benefit from moving compared to women, then we will conclude that the household's behavior is not consistent with a unitary model and conclude instead that households put less weight on income earned by the woman, with $0 < \beta < 1$.

These propositions thus make clear that men disproportionately benefiting from migration does not on its own conflict with predictions from a standard unitary household model when there are pre-existing gender earnings gaps. Intuitively, if the returns to migration are similar across the income distribution (in percentage terms), then men and women who move as couples will tend to experience increased earnings inequality within the household. In order to rule out a unitary model, we need to "zoom in" on the households near $s = 0.5$.

These theoretical results therefore motivate additional empirical specifications testing for heterogeneity in the effects of migration by the female share of household income prior to the move. Specifically, they imply we should expand the earnings regression models that estimate the earnings effects of migration to estimate how the earnings effects of migration vary with s.

5.2 Heterogeneity in the Effects of Migration on Earnings by Female Share of Household Income

Our results based on the full sample indicate that men realize significant positive returns from moving, while women are more likely to leave the workforce in the first years after the move. Based on the results in the previous subsection, we now examine how the returns to moving differ based on each individual's predicted share of household income.

In order to operationalize the additional empirical tests suggested by the model, we first construct a measure of (predicted) female share of household income. To do this, we estimate predicted income from a regression model. Specifically, we run a regression on a random sample of the full population of employed individuals in each country aged 25-54. The regression model relates log annual earnings to a large set of controls: potential experience dummies, child dummies, education dummies, and year dummies.[15] In Sweden, we also include detailed indicators for the college majors for the individuals who attended either college and vocational training, and we interact these college major indicators with the education dummies in the prediction model.

[15]The three education levels we use are high school, vocational training, and college.

We then use these regression models to construct a measure of predicted income in the year prior to the move for each member of the household, and we calculate the predicted female share of household income in both of our samples. Figures OA-6 and OA-7 show the distribution of predicted incomes for the men and women in our sample, and the predicted female share using this prediction model. We use the predicted female share of household income ($\hat{s}$) as our empirical proxy for the s in the model.

We choose to use predicted female share rather than the actual share partly because our layoff results indicate a clear gender-specific effect of layoffs on the probability of moving, so women with very high income shares in the years right before a move may be disproportionately made up of households where the man was recently laid off. In these households, the fact that the man disproportionately benefits from moving could mechanically come from a kind of "mean revision" arising from the layoff event that occurred prior to the migration decision. Additionally, actual earnings may not reflect an individual's true earnings potential, particularly for women; for example, Bertrand et al. (2015) find that relative income concerns affect actual earnings, as women may prefer to earn less to avoid out-earning their spouses. Our use of a predicted female earnings share measure is designed to address both of these concerns.[16]

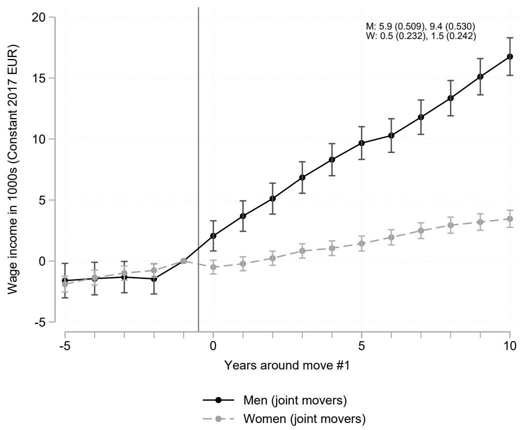
As a result, we focus on households with similar predicted income based on education and experience, and we assume that households with similar potential income have similar returns to migration. These are the households we want to "zoom in" on in order to estimate the earnings effects for households at or near $\hat{s} = 0.5$.

To get an initial sense of how the earnings effects of moving vary with $\hat{s}$, we first divide our sample into couples where the man has the higher predicted share of household income and those where the woman has the higher share. The results are shown in Figure 6. This figure shows that the gap between men's and women's wage income is a bit smaller when women have a larger (i.e., greater than 50%) predicted share of household income, although the point estimates suggest that women still earn slightly less than men. This implies that on average men benefit more from relocation than women for households with $\hat{s} < 0.5$, but women do not benefit more from relocation than men for households with $\hat{s} > 0.5$. Appendix Figure OA-4 shows that we still do not find evidence that women benefit more from relocation than men when $\hat{s} > 0.5$ using a gender-specific measure of predicted income (as compared to the gender-blind prediction that we use in our baseline analysis). Taken together, these results are our first pieces of evidence that $\beta < 1$ in both countries.

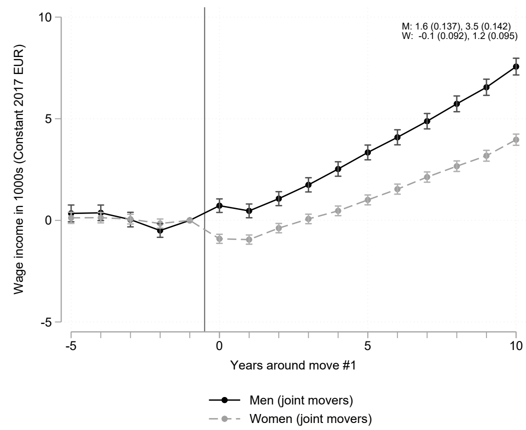
[16] Additionally, in our model where households behave "as if" they value the income earned by the woman less than the income earned by the man, women may choose to work less and earn less precisely because of this "discounting" of the woman's income within the household. That is, even when men and women have the same potential income, there will be a gender earnings gap within the household when $\beta < 1$ allowing for endogenous labor supply responses.

Figure 6: Impact of Move on Wage Income – By Gender-blind Predicted Female Share of HH Income

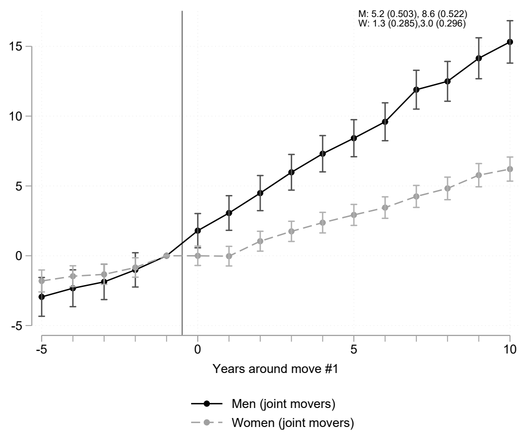
(a) Female Share of HH Income < 50%, Germany



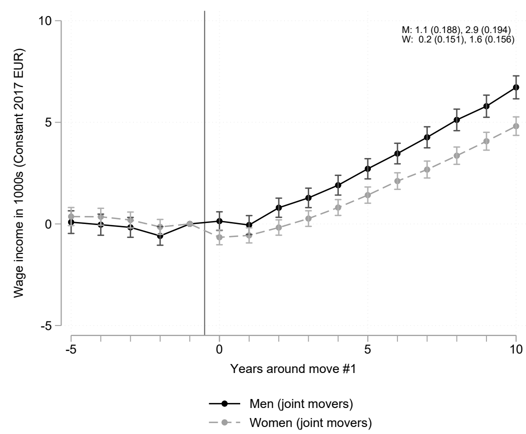
(b) Female Share of HH Income < 50%, Sweden



(c) Female Share of HH Income ≥ 50%, Germany



(d) Female Share of HH Income ≥ 50%, Sweden



Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t = 0$ to $t = 5$ and $t = 10$), in this order, for men (M) and women (W). Gender-blind predicted earnings are calculated by regressing men's log individual income on experience indicators and education level interacted with field of study, in a way that men and women with the same covariates have the same predicted wage income.

In order to estimate how the earnings effects of migration vary with $\hat{s}$, we estimate flexible spline specifications that interact spline functions of $\hat{s}$ with indicator variables capturing the years after the move. The spline specifications are used to construct predicted values of the average earnings effects of migration at $\hat{s} = 0.4$ and $\hat{s} = 0.5$ for men and women. These results are summarized in Table 4 below. Columns (1) and (2) show the results for Germany, and columns (3) and (4) show the results for Sweden.

Table 4: How Do the Effects of Moving by Gender Vary with the Predicted Female Share of Household Income?

	Germany		Sweden	
Predicted Female Share of Household Income, $\hat{s}$	Men (1)	Women (2)	Men (3)	Women (4)
$\hat{s} = 0.4$	7.95	0.90	3.18	-0.14
	(.)	(.)	(.)	(.)
$\hat{s} = 0.5$	5.84	2.20	1.01	0.675
	(.)	(.)	(.)	(.)
Full sample	8.24	1.91	3.29	1.24
	(0.35)	(0.18)	(0.12)	(0.08)

Notes: This table presents estimates from spline regressions on the earnings effects of moving by gender, allowing for the effects of moving to vary with the predicted female share of household income. The final row reports the estimates from the full sample for comparison. These results are based on gender-blind earnings predictions.

Comparing across the columns, we see that in Sweden there is a smaller baseline gender gap (in the years prior to migration) and a lower migration rate compared to Germany. In both countries, at $\hat{s} = 0.4$ there are large differences by gender. For these households, men's earnings increase by 10-15 percent in both countries, while women's income actually declines in Sweden and does not change in Germany.

Note the model described above can generate average declines in earnings for women even in a unitary model if there is a large variance in idiosyncratic mobility costs across households. Intuitively, if there are many other reasons why households move besides to increase labor earnings, then sometimes one or both members in the household will choose to move even though their income declines, and this is more likely to happen for women compared to men at $\hat{s} = 0.4$, even in unitary households.[17]

Turning to $\hat{s} = 0.5$, we see in both countries the average return to migration is lower for men and higher for women (compared to $\hat{s} = 0.4$), but a gender gap remains at $\hat{s} = 0.5$ in both countries. This is another piece of evidence against a standard unitary model explaining our results. The unitary model would predicted at $\hat{s} = 0.5$ that the average return to should be the same for men and women. The gap does "converge more" between men and women in Sweden compared to Germany, which is our first piece of evidence that households may deviate less from unitary model in Sweden compared to Germany (i.e., β is closer to 1).

[17] While the theoretical model focuses on a single mobility cost parameter c, in our model-based estimation we will allow for heterogeneity in household mobility costs by specifying a distribution of mobility costs alongside a distribution of returns to migration.

5.3 Model-Based Estimation

We now use the moments and estimates in the table to estimate the model parameters. We first calibrate the baseline distribution of income prior to migration in both countries. This requires fitting log normal income distribution for men and women in both countries. These results are reported in Panel A of Table 5. Consistent with the results in Table 4 in the previous subsection, there is a larger baseline gender gap in Germany as compared to Sweden.

Table 5: Model Parameter Estimates

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Mean log income, men	3.78	2.99
Standard deviation of log income, men	0.43	0.51
Mean log income, women	3.37	2.81
Standard deviation of log income, women	0.67	0.70
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	-0.10	-0.32
Standard deviation in the returns to migration, σ_r	0.34	0.25
Mean household mobility cost, μ_c	0.25	-0.15
Standard deviation of household mobility cost, σ_c	0.15	1.43
Relative weight on woman's income compared to man's income, β	0.63	0.86

Notes: Panel A displays the mean and standard deviation of log income in the year prior to the move for the full sample of movers. These values are used to calibrate the parameters of the log normal income distribution. Panel B displays the model-based estimates for both countries based on a simple equal-weighted minimum distance estimator, using as moments the average migration rate and the effects of moving at $\hat{s} = 0.4$ and $\hat{s} = 0.5$ reported in Table 4.

With these parameters calibrated, there are five remaining model parameters: the mean and variance parameters governing the returns to migration for men and women (μ_m and σ_m), the mean and variance parameters governing the household's idiosyncratic mobility cost (μ_c and σ_c), and the non-unitary household parameter β.

To identify and estimate these five model parameters, we use the following five moments: the migration rate (share of households moving during the sample period), the average returns to migration for men and women at $\hat{s} = 0.4$, and the average returns to migration for men and women at $\hat{s} = 0.5$. Intuitively, if $\beta = 1$, then the average returns to migration for men and women at $\hat{s} = 0.5$ should be the same, so we lose one moment and one parameter. This tells us that the "gap" in average returns to migration at $\hat{s} = 0.5$ primarily identifies the parameter β. Varying σ_c changes the average migration rate, but does not affect the average returns to migration (conditional on moving), so the migration rate primarily identifies the parameter σ_c. The identification of the other three parameters is more subtle, but they are jointly identified by the relative gaps between men and women at $\hat{s} = 0.4$ compared to $\hat{s} = 0.5$, given β.

To estimate the model parameters, we simulate the model a large number of times and search for the combination of model parameters that minimize the sum of the squared distance between the moments and the simulated values of the moments from the model (since σ_c can always be chosen to target a given migration rate, we search over the other four parameters and then choose σ_c to match migration rate exactly). The model-based parameters are reported in Panel B of Table 5. Table 6 compares the actual moments and the simulated moments at the chosen model parameters, which shows that the model has a good fit in both countries.

Turning to the estimated parameters, we see that the returns to migration is "shifted down" in Sweden compared to Germany, which is consistent with both the lower estimated average returns to moving. Since the migration rate is not that much lower in Sweden, however, we need the mobility costs to be more heterogeneous in Sweden in order to generate enough migration in the model to match the data.

Our primary parameter of interest is the β parameter, which is estimated to be $\beta = 0.86$ in Sweden and $\beta = 0.56$. One way to assess the importance of $\beta < 1$ is to re-simulate the model with $\beta = 1$, holding the other parameters constant. Panel C of Table 6 shows that this results in a worse model fit, particularly for the $\hat{s} = 0.5$ households. An alternative is to re-estimate the model restricting $\beta = 1$; column (4) of Table 6 shows that this model also has a worse fit, particularly for Germany.

The conclusion from the model-based estimation is therefore that the earnings effects of migration in both countries are difficult to reconcile with a standard unitary household model, and the earnings effects at different predicted female shares of household income suggest that households in both countries place less weight on income earned by woman compared to man, particularly in Germany.

The larger departure from the unitary model in Germany is interesting because Germany also has a larger baseline gender gap (and, as we discuss later, a larger female "child penalty"). This raises the possibility that the baseline gender gap itself may be due to the same factors that lead households to seemingly "under-react" to women's potential returns from relocation. We conclude this section by using the estimated model to carry out two additional exercises: we use the model to simulate the effects of job layoffs on migration and the effects of childbirth on earnings.

Table 6: Assessing Model Fit

	Germany		Sweden	
Predicted Female Share of Household Income, $\hat{s}$	Men (1)	Women (2)	Men (3)	Women (4)
Panel A: Empirical Estimates				
$\hat{s} = 0.4$	7.95	0.90	3.18	-0.14
$\hat{s} = 0.5$	5.84	2.20	1.01	0.68
Panel B: Simulated Moments from Baseline Model				
$\hat{s} = 0.4$	7.47	1.02	3.54	-0.40
$\hat{s} = 0.5$	5.23	2.33	1.25	0.74
χ^2 goodness-of-fit statistic	0.116		0.587	
Panel C: Simulated Moments Setting $\beta = 1$ (holding other parameters constant)				
$\hat{s} = 0.4$	6.58	2.34	3.33	-0.93
$\hat{s} = 0.5$	3.96	3.70	0.94	1.22
χ^2 goodness-of-fit statistic	4.168		4.899	
Panel D: Simulated Moments Restricting to $\beta = 1$ (re-estimating other parameters)				
$\hat{s} = 0.4$	7.34	1.53	2.81	-0.62
$\hat{s} = 0.5$	4.17	4.07	1.15	0.71
χ^2 goodness-of-fit statistic	2.564		1.703	

Notes: This table presents the empirical estimates of the effects of moving at $\hat{s} = 0.4$ and $\hat{s} = 0.5$ and compares to the baseline model estimates and alternative model estimates setting $\beta = 1$ and either holding other parameters constant or re-estimating the other model parameters.

5.4 Additional Implications of $\beta < 1$: Gender Differences in Effects of Job Layoffs on Relocation and Gender Differences in Child Penalties

An additional way to assess the fit of the model with the estimated $\beta < 1$ parameter is to simulate an exogenous decline in male or female income (from job separation caused by mass layoff), and then predict the change in the probability of moving depending on whether or not the male or female was laid off. We can then compare these results to the reduced-form effects above. This is an "out-of-sample" test of model fit because the effects of job layoff on the probability of relocating by gender were not directly targeted in the model-based estimation. To do this, we simulate the model at the parameters estimated in each country and we exogenously reduce income by the man or woman by 20 percent and then estimate the resulting change in the probability of moving. The results in Panel A of Table 7 show that the model can accurately reproduce a gender gap in the effects of a job layoff on the probability of moving. The model somewhat under-predicts the gender gap in Germany and somewhat over-predicts the gender gap in Sweden, but this could come from the fact that we currently assume the exogenous income change is the same in both countries.

Lastly, we use our estimated model to simulate the change in earnings following the birth of the couple's first child to see how much our estimated $\beta < 1$ parameter can account for the female "child penalty" in both countries. Specifically, we compare our simulated results to the results from Kleven et al. (2019b) that estimate the child penalty in a large number of countries. They find that the child penalty is much larger in Germany, and we also find a larger departure from $\beta = 1$ based on the earnings responses to relocation. One interpretation of the child penalty is that the household puts less weight on income declines by the woman (as compared to the man), which means that even if the man and woman in a household have equal ability in child-rearing, the household may still choose to have the woman reduce her hours in the formal labor market. The Appendix formalizes this argument and shows that the child penalty should be closely related to $(1 - \beta)$ in this case. We do this by extending the model in Andresen and Nix (2022) to allow for $\beta < 1$, and Panel B of Table 7 shows that this simulated model can account for most of the female "child penalty" in both Germany and Sweden, and can also account for most of the difference between Germany and Sweden. In other words, the greater deviation from unitary model in Germany can account for most of the larger child penalty according to our simulated model.

Table 7: Model-Based Simulations

	Germany		Sweden	
	Men	Women	Men	Women
	(1)	(2)	(3)	(4)
Panel A: Proportional Change in Probability of Moving After Layoff				
Empirical estimate	1.83	1.24	1.89	0.88
Model-based simulation	1.61	1.29	1.95	1.58
Panel B: Proportional Change in Earnings After Birth of First Child				
Empirical estimate from Kleven et al. (2019a)	-0.02	-0.61	-0.06	-0.26
Model-based simulation	-0.04	-0.48	-0.07	-0.19
Implied share of Female "child penalty" accounted for the country-specific β estimate		78.7%		71.5%

Notes: Panel A uses baseline model-based estimates to simulate changes in the probability of moving after an exogenous job displacement. Panel B simulates change in earnings after birth of first of child to compare the implied changes (at estimated country-specific β) to the actual changes estimated in Kleven et al. (2019a).

6 Conclusion

Over the past half a century, women have made great strides in the labor market. However, despite substantial gender convergence, there are still large differences between men and women. In this paper, we investigate an aspect that contributes to gender differences in the labor market which has not received much attention in the recent literature: gender differences in the returns to moving. Using administrative data from Germany and Sweden, we use an event study design to estimate the labor market effects of couples' long-distance moves, and we find that men's earnings increase significantly after a long-distance move, and women's earnings increase by less (if at all). These results echo some of the results in previous studies (see, e.g., Blackburn 2010a; Cooke et al. 2009; LeClere and McLaughlin 1997; Sandell 1977; Blackburn 2010b; Cooke 2003; Spitze 1984; Rabe 2009), but the unusually large and representative sample of opposite-sex couples in our analysis provides new evidence of this gender divergence. While we find that men benefit almost exclusively through higher wages, women's losses are mostly due to exiting the labor market or being employed for fewer days of the year.

Using a model of household decision-making where households "discount" the income earned by the woman compared to the man, we test and reject the unitary model in both countries, with larger departures in Germany compared to Sweden. Overall, we conclude that a gender norm that prioritizes men's career advancement can simultaneously (and parsimoniously) account for three different gender differences in labor market outcomes: the earnings effects of relocation, the probability of moving following a job layoff, and the earnings effects of the birth of a child (the so-called "child penalty"). Of course, it is hard to fully rule out explanations based on gender differences in preferences (e.g., preferences for child-rearing, preferences for leisure, preferences for part-time work or flexible hours), but we interpret our model-based estimates as potentially suggesting a unifying explanation that households systematically pass up opportunities to maximize lifetime household income because households behave "as if" income earned by the woman is worth less than income earned by the man. If true, this is hard to square with many models of efficient household decision-making.

We conclude by briefly mentioning several areas of future work. First, we make several simplifying assumptions in the model. For example, we assume away heterogeneity in the β parameter. This is done to make the identification as transparent as possible, but it may be possible to estimate a richer model where β can vary with observed and unobserved household characteristics. Second, we focus on two countries with readily-available administrative data and fairly different labor market institutions, but we think our framework can be easily implemented in other countries. If we are right that the female "child penalty" is driven at least in part by our β parameter, then one should see larger departures from the unitary model in countries with larger child penalties. Lastly, we conjecture that our model may be consistent with certain household bargaining models with limited commitment, and it would be interesting to try to make this connection more precise. For the questions addessed in this paper, we did not need a micro-foundation of where the $\beta < 1$ parameter is coming from, but for other questions it may be useful to give more details of exactly how the households come to treat women's income as less valuable than men's.

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A Online Appendix

A.1 Proofs of Theoretical Results in Main Text

Proposition 1 *If $\mu_M > \mu_F$ and all households are unitary households, then the expected return to moving (conditional on moving) is larger for men than women: $E[\Delta y_M - \Delta y_F | \Delta y_M + \Delta y_F > c] > 0$.*

Proof. [To be completed]

Lemma 1 *If $\mu_M > \mu_F$ and all households are unitary households, then the expected return to moving (conditional on moving) is larger for men than women for any household with $0 < s < 0.5$; i.e., for all $0 < s < 0.5$, $E[\Delta y_M - \Delta y_F | s, \Delta y_M + \Delta y_F > c] > 0$.*

Proof. To start, we expand the expectation, $E[\Delta y_M - \Delta y_F | s, \Delta y_M + \Delta y_F > c]$.

$$
\begin{aligned}
\Delta y_M - \Delta y_F &= (y_{M2} - y_{M1}) - (y_{F2} - y_{F1}) \\
&= (1 + \varepsilon_{M2})(1 - s)y_1 - (1 - s)y_1 - (1 + \varepsilon_{F2})sy_1 + sy_1 \\
&= \varepsilon_{M2}(1 - s)y_1 - \varepsilon_{F2} s y_1 \\
\Delta y_M + \Delta y_F &= (y_{M2} - y_{M1}) + (y_{F2} - y_{F1}) \\
&= (1 + \varepsilon_{M2})(1 - s)y_1 - (1 - s)y_1 + (1 + \varepsilon_{F2})sy_1 - sy_1 \\
&= \varepsilon_{M2}(1 - s)y_1 + \varepsilon_{F2} s y_1 \\
\implies E[\Delta y_M - \Delta y_F \mid s, \Delta y_M + \Delta y_F > c] &= E[\varepsilon_{M2}(1 - s)y_1 - \varepsilon_{F2} s y_1 \mid s, \varepsilon_{M2}(1 - s)y_1 + \varepsilon_{F2} s y_1 > c]
\end{aligned}
$$

We want to show that when $0 < s < 0.5$, $E[\varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2} s y_1 \mid \varepsilon_{M2}(1-s)y_1 + \varepsilon_{F2} s y_1 > c] > 0$. Let $X = \varepsilon_{M2}(1 - s)y_1$ and $Y = \varepsilon_{F2} s y_1$, with their distributions defined below. Recall that $\varepsilon_{i2} \sim N(\mu_r, \sigma_r^2)$. We assume $cov(X, Y) = 0$.

$$
\begin{aligned}
X &= \varepsilon_{M2}(1 - s)y_1 & \qquad Y &= \varepsilon_{F2} s y_1 \\
&\sim N((1 - s)\mu_r y_1, ((1 - s)y_1\sigma_r)^2) & &\sim N(s\mu_r y_1, (s y_1 \sigma_r)^2)
\end{aligned} \tag{2}
$$

With this substitution, we can rewrite the expectation to be $E[X - Y \mid X + Y > c]$, which allows us to use the derivation from A.2.2, equation (6).

$$\begin{aligned}
E[X-Y|X+Y>c] &= \mu_X - \mu_Y + \lambda\left(\frac{c-\mu_X-\mu_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right)\left[\frac{\sigma_X^2-\sigma_Y^2}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right] \\
&= (1-s)\mu_r y_1 - s\mu_r y_1 + \lambda\left(\frac{c-(1-s)\mu_r y_1 - s\mu_r y_1}{\sqrt{((1-s)y_1\sigma_r)^2+(sy_1\sigma_r)^2}}\right)\left[\frac{((1-s)y_1\sigma_r)^2-(sy_1\sigma_r)^2}{\sqrt{((1-s)y_1\sigma_r)^2+(sy_1\sigma_r)^2}}\right] \\
&= \mu_r y_1(1-2s) + \lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right)\left[\frac{\sigma_r^2 y_1^2[(1-s)^2-s^2]}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right] \\
&= \mu_r y_1(1-2s) + \lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right)\left[\frac{\sigma_r y_1(1-2s)}{\sqrt{(1-s)^2+s^2}}\right]
\end{aligned}$$

The expression we end up with is given below:

$$E[X-Y|X+Y>c] = (1-2s)\left[\mu_r y_1 + \lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right)\left[\frac{\sigma_r y_1}{\sqrt{(1-s)^2+s^2}}\right]\right] \tag{3}$$

When $0 < s < 0.5$, the first term, $1-2s$, is greater than zero. Inside the brackets, $\mu_r y_1 > 0$ because the mean income in the second period and household income of the first period is assumed to be greater than zero. The Inverse Mills Ratio, $\lambda(\cdot)$ is always greater than zero. And lastly the fraction $\frac{\sigma_r y_1}{\sqrt{(1-s)^2+s^2}} > 0$ because $\sigma_r > 0$ and the income is assumed to be greater than zero.

This implies $E[X - Y \mid X + Y > c] > 0$, proving that the expected return to moving conditional on moving is larger for men than women for any household with $0 < s < 0.5$.

Proposition 2 *If $\mu_M > \mu_F$ and all households are unitary households, then the expected return to moving (conditional on moving) for men and women is equal for households at $s = 0.5$; i.e., $E[\Delta y_M - \Delta y_F | s = 0.5, \Delta y_M + \Delta y_F > c] = 0$.*

Proof. Note that the expectation, $E[\Delta y_M - \Delta y_F | s = 0.5, \Delta y_M + \Delta y_F > c]$, in this proposition is the same as in 1, but rather than the expression being greater than zero at $0 < s < 0.5$, we want to show that the expression is equal to zero at $s = 0.5$.

Following the same steps to simplify the expectation as in 1, we get equation (3) which is reproduced below.

$$E[X-Y|X+Y>c] = (1-2s)\left[\mu_r y_1 + \lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right)\left[\frac{\sigma_r y_1}{\sqrt{(1-s)^2+s^2}}\right]\right]$$

When $s = 0.5$, the first term, $1-2s$, is equal to zero which implies $E[X-Y \mid X+Y > c] = 0$, proving that the expected return to moving conditional on moving is the same for the man and woman for any household with $s = 0.5$.

Proposition 3 *If $\mu_M > \mu_F$ and all households are non-unitary households with $0 < \beta < 1$, then the expected return to moving (conditional on moving), then $E[\Delta y_M - \Delta y_F | s = 0.5, \Delta y_M + \beta \Delta y_F > c] > 0$ with the expectation approaching 0 as β approaches 1 from below.*

Proof. To start, we expand the expectation, $E[\Delta y_M - \Delta y_F | s, \Delta y_M + \beta \Delta y_F > c]$.

$$\begin{aligned}
\Delta y_M - \Delta y_F &= (y_{M2} - y_{M1}) - (y_{F2} - y_{F1}) \\
&= \varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2} s y_1 \\
\Delta y_M + \beta \Delta y_F &= (y_{M2} - y_{M1}) + \beta(y_{F2} - y_{F1}) \\
&= (1+\varepsilon_{M2})(1-s)y_1 - (1-s)y_1 + \beta(1+\varepsilon_{F2}) s y_1 - \beta s y_1 \\
&= \varepsilon_{M2}(1-s)y_1 + \beta \varepsilon_{F2} s y_1 \\
\implies E[\Delta y_M - \Delta y_F \mid s, \Delta y_M + \beta \Delta y_F > c] &= E[\varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2} s y_1 \mid s, \varepsilon_{M2}(1-s)y_1 + \beta \varepsilon_{F2} s y_1 > c]
\end{aligned}$$

We want to show that when $s = 0.5$, $E[\varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2} s y_1 \mid s, \varepsilon_{M2}(1-s)y_1 + \beta \varepsilon_{F2} s y_1 > c] > 0$. Using the same substitutions for X and Y as in 1, equation (2) at $s = 0.5$, we have $X, Y \sim N(0.5\mu_r y_1, ((0.5 y_1 \sigma_r)^2)$.

Rewriting the expectation to fit the form, $E[X - Y \mid X + bY > c]$, and using the results from A.2.3, equation (7), we plug in our substitutions for X, Y.

$$\begin{aligned}
E[X-Y \mid X+bY > c] &= \mu_X - \mu_Y + \lambda\left(\frac{c - \mu_X - b\mu_Y}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right)\left[\frac{\sigma_X^2 + (b^3 - 2b^2)\sigma_Y^2 + (b-1)\sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right] \\
&= \lambda\left(\frac{c - 0.5\mu_r y_1 - \beta 0.5\mu_r y_1}{\sqrt{(0.5y_1\sigma_r)^2 + \beta^2(0.5y_1\sigma_r)^2}}\right)\left[\frac{(0.5y_1\sigma_r)^2 + (\beta^3 - 2\beta^2)(0.5y_1\sigma_r)^2}{\sqrt{(0.5y_1\sigma_r)^2 + \beta^2(0.5y_1\sigma_r)^2}}\right] \\
&= \lambda\left(\frac{c - 0.5\mu_r y_1(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{(0.5y_1\sigma_r)^2(1+\beta^3 - 2\beta^2)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right]
\end{aligned}$$

The expression we end up with at $s = 0.5$ is given below:

$$E[X-Y \mid X+\beta Y > c] = \lambda\left(\frac{c - 0.5\mu_r y_1(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{0.5y_1\sigma_r(1+\beta^3 - 2\beta^2)}{\sqrt{1+\beta^2}}\right] \tag{4}$$

To prove the proposition, we want to show that the expression above is positive. The Inverse Mills Ratio, $\lambda(\cdot)$, is always greater than zero. And for $0 < \beta < 1$, the numerator in the second term, $0.5y_1\sigma_r(1+\beta^3-2\beta^2)$, is in the open interval $(0, 0.5y_1\sigma_r)$. Because $0.5y_1\sigma_r > 0$, we have shown that $E[X-Y|X+\beta Y > c] > 0$, proving that the expected return to moving conditional on moving is the larger for the man and woman for any household with $s = 0.5$ and $0 < \beta < 1$.

Additionally, we want to show that the expectation approaches 0 as β approaches 1. We can do this by taking the limit of the expectation at $s = 0.5$ below:

$$\begin{aligned}
\lim_{\beta\to 1} E[X - Y \mid X + \beta Y > c] &= \lim_{\beta\to 1} \lambda\left(\frac{c - 0.5\mu_r y_1(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{0.5y_1\sigma_r(1+\beta^3-2\beta^2)}{\sqrt{1+\beta^2}}\right] \\
&= \lambda\left(\frac{c - 0.5\mu_r y_1(1+1)}{0.5y_1\sigma_r\sqrt{1+1^2}}\right)\left[\frac{0.5y_1\sigma_r(1+1^3-2(1))^2)}{\sqrt{1+1^2}}\right] \\
&= \lambda\left(\frac{c - 0.5\mu_r y_1(1+1)}{0.5y_1\sigma_r\sqrt{2}}\right)\left[\frac{0.5y_1\sigma_r(0)}{\sqrt{2}}\right] \\
&= 0
\end{aligned}$$

A.2 Additional Theoretical Results

In the section below, general derivations are provided based on the following normally distributed random variables.[18] Let $X \sim N(\mu_X, \sigma_X^2)$, $Y \sim N(\mu_Y, \sigma_Y^2)$, $X + Y \sim N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2 + 2cov(X, Y))$, and c be a constant.

A.2.1 $E[X \mid X + Y > c - \mu_X - \mu_Y]$ with $(X + Y, X)$ bivariate normal

We want to simplify to expression: $E\left[X \mid X + Y > c - \mu_X - \mu_Y\right]$. In the first step below, we standardize the expectation (e.g. $\frac{x-\mu_x}{\sigma_x}$ where x is a random variable):

$$E\left[X \mid X + Y > c - \mu_X - \mu_Y\right] = \frac{1}{\sigma_X} E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right]$$
$$E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right] = E\left[E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}}\right] \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right]$$

The last line above follows from a version of the law of iterated expectations: for any non-stochastic function $f(\cdot)$ and $X = f(W), E[Y|X] = E[E[Y|X]|X]$.

[18] Some of the results provided in this section are restatements from Heidi Williams' lecture notes on models of self selection available through MIT OpenCourseWare.

To simplify the expression further, we want to solve for $E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}}\right]$. Let $s = \frac{X+Y}{\sigma_{X+Y}}$. For simplicity, we assume $\mu_X = \mu_Y = 0$, which would allow and $s \sim N(0,1)$.

$$\begin{aligned} E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}}\right] &= \frac{1}{\sigma_X} E\left[X \mid \frac{X+Y}{\sigma_{X+Y}}\right] \\ &= \frac{1}{\sigma_X} E\left[X \mid s\right] \end{aligned}$$

We need an expression for $E[X \mid s]$, which we can derive using the facts below.

- Given a vector of random variables $X \sim N(\mu, \Sigma)$, then $AX + b \sim N(A\mu + b, A\Sigma A')$. Using this property, because X is normally distributed and $X + Y$ is normally distributed, we know that $\binom{X+Y}{X}$ are jointly normally distributed.
- Given $\binom{X}{Y} \sim N\left(\binom{\mu_X}{\mu_Y}, \begin{pmatrix} \sigma_X^2 & \sigma_{X,Y} \\ \sigma_{X,Y} & \sigma_Y^2 \end{pmatrix}\right)$, then $(Y \mid X = x) \sim N\left(\mu_Y + \rho_{X,Y}\left(\frac{\sigma_Y}{\sigma_X}\right)(x - \mu_X,), \sigma_Y^2(1 - \rho_{X,Y}^2)\right)$. Applying this property to X and $X + Y$, because they are jointly normal, we have $E\left[X \mid X + Y\right] = \rho_{X,X+Y}\left(\frac{\sigma_X}{\sigma_{X+Y}}\right)(X + Y) = \frac{\sigma_{X,X+Y}}{\sigma_{X+Y}^2}(X + Y)$.

Adapting those facts to our substitution with s, we have $E[X \mid s] = \rho_{X,s}\left(\sigma_X/\sigma_S\right) \cdot s = (\sigma_{X,s}/\sigma_s^2) \cdot s$.

Continuing the substitution,

$$\begin{aligned} E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}}\right] &= \frac{1}{\sigma_X} E\left[X \mid s\right] \\ &= \frac{1}{\sigma_X} \frac{cov(X,s)}{\sigma_s^2} \cdot s \\ &= \frac{1}{\sigma_X} \left[\frac{cov(X, \frac{X+Y}{\sigma_{X+Y}})}{\sigma_s^2}\right] \cdot s \\ &= \frac{1}{\sigma_X} \frac{\frac{1}{\sigma_{X+Y}} cov(X, X+Y)}{1} \cdot \frac{X+Y}{\sigma_{X+Y}} \\ &= \frac{cov(X, X+Y)}{\sigma_X \cdot \sigma_{X+Y}} \frac{X+Y}{\sigma_{X+Y}} \\ &= \rho_{X,X+Y} \frac{X+Y}{\sigma_{X+Y}} \end{aligned}$$

Plugging these results back into the first expression at the beginning of the section:

$$\begin{aligned} E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right] &= E\left[E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}}\right] \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right] \\ &= E\left[\rho_{X,X+Y} \frac{X+Y}{\sigma_{X+Y}} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right] \\ &= \rho_{X,X+Y} E\left[\frac{X+Y}{\sigma_{X+Y}} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c - \mu_X - \mu_Y}{\sigma_{X+Y}}\right] \end{aligned}$$

The expectation in the last equation above follows a truncated normal distribution, so we can rewrite it as:

$$E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c-\mu_X-\mu_Y}{\sigma_{X+Y}}\right] = \rho_{X,X+Y}\frac{\phi(\frac{c-\mu_X-\mu_Y}{\sigma_{X+Y}})}{1-\Phi(\frac{c-\mu_X-\mu_Y}{\sigma_{X+Y}})} \tag{5}$$

This result will be used to simplify expressions in A.2.2 and A.2.3.

A.2.2 $E[X-Y \mid X+Y>c]$ with (X,Y) bivariate normal

We want to calculate $E[X-Y|X+Y>c]$ where c is a constant.

$$E[X-Y|X+Y>c] = 2E[X|X+Y>c] - E[X+Y|X+Y>c]$$

We solve for each term separately, starting with the first term: $E[X|X+Y>c]$. Redefine $X = \mu_X+\varepsilon_X$ with $\varepsilon_X \sim N(0,\sigma_X^2)$, $Y = \mu_Y+\varepsilon_Y$ with $\varepsilon_Y \sim N(0,\sigma_Y^2)$. It follows that $\varepsilon_X+\varepsilon_Y \sim N(0,\sigma_X^2+\sigma_Y^2+2cov(X,Y))$.

$$\begin{aligned}
E[X|X+Y>c] &= E[\mu_X+\varepsilon_X|(\mu_X+\varepsilon_X)+(\mu_Y+\varepsilon_Y)>c] \\
&= \mu_X + E[\varepsilon_X|\varepsilon_X+\varepsilon_Y > c-\mu_X-\mu_Y] \\
&= \mu_X + \sigma_X E\left[\frac{\varepsilon_X}{\sigma_X}|\frac{\varepsilon_X+\varepsilon_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}} > \frac{c-\mu_X-\mu_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}}\right]
\end{aligned}$$

To simplify the second term above, we apply the result derived in A.2.1, equation (5). Let $z = \frac{c-\mu_X-\mu_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}}$ and $\lambda(z) = \frac{\phi(z)}{1-\Phi(z)}$.

$$\begin{aligned}
E[X|X+Y>c] &= \mu_X + \sigma_X\rho_{\varepsilon_X,\varepsilon_X+\varepsilon_Y}\lambda(z) \\
&= \mu_X + \sigma_X\frac{cov(\varepsilon_X,\varepsilon_X+\varepsilon_Y)}{\sigma_{\varepsilon_X}\cdot\sigma_{\varepsilon_X+\varepsilon_Y}}\lambda(z) \\
&= \mu_X + \sigma_X\frac{var(\varepsilon_X)+cov(\varepsilon_X,\varepsilon_Y)}{\sigma_{\varepsilon_X}\cdot\sigma_{\varepsilon_X+\varepsilon_Y}}\lambda(z) \\
&= \mu_X + \sigma_X\frac{\sigma_X^2+\sigma_{X,Y}}{\sigma_X\cdot\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}}\lambda(z) \\
&= \mu_X + \frac{\sigma_X^2+\sigma_{X,Y}}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}}\lambda(z)
\end{aligned}$$

The second term, $E[X+Y|X+Y>c]$, follows a truncated normal distribution which is given by:

$$E[X+Y|X+Y>c] = \mu_X + \mu_Y + \sqrt{\sigma_X^2 + \sigma_Y^2 + 2cov(X,Y)}\lambda(z)$$

Combining the terms together, we get:

$$\begin{aligned}
E[X-Y|X+Y>c] &= 2E[X|X+Y>c] - E[X+Y|X+Y>c] \\
&= 2\left[\mu_X + \frac{\sigma_X^2 + \sigma_{X,Y}}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}}\lambda(z)\right] - \mu_X - \mu_Y - \sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}\lambda(z) \\
&= 2\mu_X - \mu_X - \mu_Y + \lambda(z)\left[\frac{2\sigma_X^2 + 2\sigma_{X,Y}}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}} - \sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}\right] \\
&= \mu_X - \mu_Y + \lambda(z)\left[\frac{2\sigma_X^2 + 2\sigma_{X,Y} - \sigma_X^2 - \sigma_Y^2 - 2\sigma_{X,Y}}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right]
\end{aligned}$$

The final simplified form for the expression, $E[X-Y|X+Y>c]$, is given below:

$$E[X-Y|X+Y>c] = \mu_X - \mu_Y + \lambda\left(\frac{c-\mu_X-\mu_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right)\left[\frac{\sigma_X^2-\sigma_Y^2}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right] \tag{6}$$

A.2.3 $E[X-Y|X+bY>c]$ with (X,Y) bivariate normal

We want to calculate $E[X-Y|X+bY>c]$ where $0<b<1$ and c is a constant.

$$E[X-Y|X+bY>c] = 2E[X|X+bY>c] - E[X+bY|X+bY>c] - (1-b)E[Y|X+bY>c]$$

We solve for each term above separately, starting with the first term: $E[X|X+bY>c]$. Redefine $X=\mu_X+\varepsilon_X$ with $\varepsilon_X \sim N(0,\sigma_X^2)$. Similarly, let $bY = b\mu_Y + \varepsilon_Y$ where $\varepsilon_Y \sim N(0, b^2\sigma_Y^2)$. It follows that $\varepsilon_X + \varepsilon_Y \sim N(0, \sigma_X^2 + b^2\sigma_Y^2 + 2cov(X,Y))$.

$$\begin{aligned}
E[X|X+bY>c] &= E[\mu_X + \varepsilon_X \mid (\mu_X+\varepsilon_X) + (b\mu_Y + \varepsilon_Y) > c] \\
&= \mu_X + E[\varepsilon_X \mid \varepsilon_X + \varepsilon_Y > c - \mu_X - b\mu_Y] \\
&= \mu_X + \sigma_X E\left[\frac{\varepsilon_X}{\sigma_X} \mid \frac{\varepsilon_X+\varepsilon_Y}{\sqrt{\sigma_X^2+b^2\sigma_Y^2+2cov(X,Y)}} > \frac{c-\mu_X-b\mu_Y}{\sqrt{\sigma_X^2+b^2\sigma_Y^2+2cov(X,Y)}}\right]
\end{aligned}$$

To simplify the second term above, we apply the result derived in A.2.1, equation (5). As in A.2.2, we let $z = \frac{c-\mu_X - b\mu_Y}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2cov(X,Y)}}$, $\lambda(z) = \frac{\phi(z)}{1-\Phi(z)}$, and apply the same steps.

$$
\begin{aligned}
E[X|X + bY > c] &= \mu_X + \sigma_X \rho_{\varepsilon_X, \varepsilon_X + \varepsilon_Y} \lambda(z) \\
&= \mu_X + \sigma_X \left(\frac{var(\varepsilon_X) + cov(\varepsilon_X, \varepsilon_Y)}{\sigma_{\varepsilon_X} \cdot \sigma_{\varepsilon_X + \varepsilon_Y}} \right) \lambda(z) \\
&= \mu_X + \left(\frac{\sigma_X^2 + \sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2cov(X,Y)}} \right) \lambda(z)
\end{aligned}
$$

The second term, $E[X + Y|X + Y > c]$, follows a truncated normal distribution and can be rewritten as:

$$
E[X + Y|X + Y > c] = \mu_X + b\mu_Y + \sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2cov(X,Y)}\lambda(z)
$$

The third and final term, $E[Y|X + bY > c]$, can be rewritten following a similar derivation to the first term.

$$
\begin{aligned}
E[Y \mid X + bY > c] &= \mu_Y + E[\varepsilon_Y \mid (\mu_X + \varepsilon_X) + (b\mu_Y + \varepsilon_Y) > c] \\
&= \mu_Y + b\sigma_Y E\left[\frac{\varepsilon_Y}{b\sigma_Y} \mid \varepsilon_X + \varepsilon_Y > c - \mu_X - b\mu_Y \right] \\
&= \mu_Y + b\sigma_Y \rho_{\varepsilon_Y, \varepsilon_X + \varepsilon_Y} \lambda(z) \\
&= \mu_Y + b\sigma_Y \frac{cov(\varepsilon_Y, \varepsilon_X + \varepsilon_Y)}{\sigma_{\varepsilon_Y} \cdot \sigma_{\varepsilon_X + \varepsilon_Y}} \lambda(z) \\
&= \mu_Y + b\sigma_Y \frac{var(\varepsilon_Y) + cov(\varepsilon_X, \varepsilon_Y)}{b\sigma_Y \cdot \sigma_{\varepsilon_X + \varepsilon_Y}} \lambda(z) \\
&= \mu_Y + \frac{b^2\sigma_Y^2 + \sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}} \lambda(z)
\end{aligned}
$$

Combining all three terms to solve the expression $E[X - Y \mid X + bY > c]$, we have:

$$
\begin{aligned}
&E[X - Y \mid X + bY > c] = \\
&= 2E[X|X + bY > c] - E[X + bY|X + bY > c] - (1 - b)E[Y|X + bY > c] \\
&= 2\left[\mu_X + \left(\frac{\sigma_X^2 + \sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right)\lambda(z)\right] - \left[\mu_X + b\mu_Y + \sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}\lambda(z)\right] \\
&\quad - (1 - b)\left[\mu_Y + \frac{b^2\sigma_Y^2 + \sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\lambda(z)\right] \\
&= 2\mu_X - \mu_X - b\mu_Y - \mu_Y + b\mu_Y + \lambda(z)\left[\frac{2\sigma_X^2 + 2\sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}} - \sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}\right. \\
&\quad \left. - \frac{b^2\sigma_Y^2 + \sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}} + \frac{b^3\sigma_Y^2 + b\sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right] \\
&= \mu_X - \mu_Y + \lambda(z)\left[\frac{2\sigma_X^2 + 2\sigma_{X,Y} - \sigma_X^2 - b^2\sigma_Y^2 - 2\sigma_{X,Y} - b^2\sigma_Y^2 - \sigma_{X,Y} + b^3\sigma_Y^2 + b\sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right]
\end{aligned}
$$

To summarize, the final derivation is given below:

$$
E[X - Y \mid X + bY > c] = \mu_X - \mu_Y + \lambda\left(\frac{c - \mu_X - b\mu_Y}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right)\left[\frac{\sigma_X^2 + (b^3 - 2b^2)\sigma_Y^2 + (b - 1)\sigma_{X,Y}}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2\sigma_{X,Y}}}\right] \tag{7}
$$

A.3 Model Extensions

Proposition 2 *If $\mu_M > \mu_F$ and all households are unitary households, then the expected return to moving (conditional on moving) for men and women is equal for households at $s = 0.5$; i.e., $E[\Delta y_M - \Delta y_F | s = 0.5, \Delta y_M + \Delta y_F > c] = 0$.*

Proof. Refer to A.1, Proposition 2.

Corollary 2.1 *Proposition 2 holds in the assortative matching case (i.e., $\rho_{\varepsilon_{M1},\varepsilon_{F1}} \neq 0$).*

Proof. Recall the substitution for X and Y from equation (2) where $X \sim N((1-s)\mu_r y_1, ((1-s)y_1\sigma_r)^2)$ and $Y \sim N(s\mu_r y_1, (sy_1\sigma_r)^2)$. Using this substitution, the expanded form for the expression, $E[\Delta y_M - \Delta y_F | \Delta y_M + \Delta y_F > c]$, is given in Lemma 1, equation (3) which is reproduced below.

$$
E[X - Y|X + Y > c] = (1 - 2s)\left[\mu_r y_1 + \lambda\left(\frac{c - \mu_r y_1}{\sigma_r y_1\sqrt{(1 - s)^2 + s^2}}\right)\left[\frac{\sigma_r y_1}{\sqrt{(1 - s)^2 + s^2}}\right]\right]
$$

Notice that X, Y, and $E[X - Y|X + Y > c]$ do not depend on any functional form assumptions on Period 1 income, which is where $\rho_{\varepsilon_{M1},\varepsilon_{F1}}$ would impact each household member's income. Therefore, assortative matching in the first period will not affect the results and Proposition 2 still holds.

Corollary 2.2 *Proposition 2 holds in the heteroskedasticity case (i.e., $\sigma_M^2 \neq \sigma_F^2$).*

Proof. We can follow the same argument laid out in Proposition 2, Corollary 2.1 looking at the substitutions for X and Y, and referring to the expectation in equation (3) above. The variances for X and Y do not depend on Period 1 variance, σ_i^2 for $i = \{M, F\}$, or any functional form assumptions on Period 1 income, so $\sigma_M^2 \neq \sigma_F^2$ would not affect the results and Proposition 2 still holds with heteroskedasticity in the first period.

Proposition 3 *If $\mu_M > \mu_F$ and all households are non-unitary households with $0 < \beta < 1$, then the expected return to moving (conditional on moving), then $E[\Delta y_M - \Delta y_F|s = 0.5, \Delta y_M + \beta\Delta y_F > c] > 0$ with the expectation approaching 0 as β approaches 1 from below.*

Proof. Refer to A.1, Proposition 3.

Corollary 3.1 *Proposition 3 holds in the assortative matching case (i.e., $\rho_{\varepsilon_M,\varepsilon_F} \neq 0$).*

Proof. From A.1, Proposition 3, the substitution for X and Y remain identical to equation (2). The final expression for $E[\Delta y_M - \Delta y_F|s = 0.5, \Delta y_M + \beta\Delta y_F > c]$ is given in equation (4), reproduced below:

$$E[X - Y \mid X + \beta Y > c] = \lambda\left(\frac{c - 0.5\mu_r y_1(1+\beta)}{0.5 y_1 \sigma_r \sqrt{1+\beta^2}}\right)\left[\frac{0.5 y_1 \sigma_r (1 + \beta^3 - 2\beta^2)}{\sqrt{1+\beta^2}}\right]$$

The random variables, X and Y, and the expectation above, do not depend on any functional form of Period 1 income, where $\rho_{\varepsilon_{M1},\varepsilon_{F1}}$ would impact each household member's income. Therefore, assortative matching in the first period will not affect the results and Proposition 3 still holds.

Corollary 3.2 *Proposition 3 holds in the heteroskedasticity case (i.e., $\sigma_{M1}^2 \neq \sigma_{F1}^2$).*

Proof. As before, we can follow the same argument laid out in Proposition 3, Corollary 3.1 looking at the substitutions for X and Y, and referring to the expectation in equation (4) above. Again, the variances for X and Y do not depend on Period 1 variance, σ_i^2 for $i = \{M, F\}$, or any functional form assumptions on Period 1 income, so $\sigma_M^2 \neq \sigma_F^2$ would not affect the results and Proposition 3 still holds with heteroskedasticity in the first period.

A.4 Model-Based Simulations

In this section, we numerically simulate the model developed in the main text to estimate how the probability of moving varies with the female share of household income and how the earnings effects of moving vary with the female share of household income. We re-simulate the model under different functional form assumptions and different assumptions on assortative mating. One conclusion from these simulations is that the theoretical results in Foged (2016) are sensitive to functional form assumptions, while the earnings effects (at $s = 0.5$ and for $s < 0.5$ remain robust). This suggests that the potential "U-shaped" pattern of household migration (as a function of the female earnings share) may be a less reliable way to infer the discount households place on income earned by the woman compared to the man.

[Simulation evidence to be added here; available upon request]

A.5 Extended Model of Child Penalty

In this section we present an extended version of the model of the child penalty in Andresen and Nix (2022) that incorporates our parameter β that governs the relative weight on income earned by the woman compared to the man. In the baseline Andresen and Nix (2022) model, a couple without children makes a joint hours decision (choosing h_M and h_F) to maximize the following household utility function

$$c + \eta_M \frac{(T - h_M)^{(1-\gamma)}}{1-\gamma} + \eta_F \frac{(T - h_F)^{(1-\gamma)}}{1-\gamma}$$

subject to the budget constraint $c \leq w_M h_M + w_F h_F$, where w_M and w_F are the wage rates for the man and woman in the household, T is the total time endowment, eta_M and eta_F are value of leisure parameters that are allowed to vary by gender, and γ determines each individual's labor supply elasticity (which is assumed to be the same for simplicity).

When a couple has a child, the household then makes the following joint hours decision (choosing h_M^C and h_F^C)

$$c + \lambda\theta + \eta_M \frac{(T - h_M)^{(1-\gamma)}}{1-\gamma} + \eta_F \frac{(T - h_F)^{(1-\gamma)}}{1-\gamma}$$

subject to the same budget constraint, with $\theta = (1/(1-\kappa) * (T - h_M^C + T - h_F^C)^{(1-\kappa)}$. Following Andresen et al., the θ parameter is interpreted as the benefit of spending time with children, and λ governs the value to the household of this time investment. (Implicitly, this stylized setup assumes that the household completely substitutes leisure time to child-rearing time after the birth of a child.)

In this setup, the change in income after having a child is defined as the "child penalty" and defined as $(w_i h_i^C - w_i h_i)/(w_i h_i)$ for $i = M, F$. In the simulations reported in the main text, we extend this model in one way which is replacing c in the household utility function with $w_M h_M + \beta * w_F h_F$, and we calibrate the model using the estimated β from the model-based estimation.

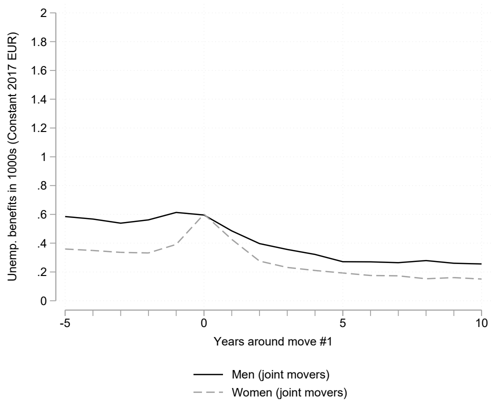
We choose $\eta_M = \eta_F = 1$, $\kappa = 0.1$, $\gamma = 0.5$, and we choose the baseline gender wage gap to be $w_F/w_M = 0.895$ in Sweden and $w_F/w_M = 0.82$ in Germany. We then simulate the model for $\lambda = 0$ and $\lambda = 0.25$ at the two different values of β and report the change in earnings for men and women in Table 7 in the main text. What this simulation exercise shows is that with no gender differences in preferences for spending time in child-rearing, and a realistic gender earnings gap, the estimated β parameters allow us to account for a majority of the so-called female "child penalty" in both Germany and Sweden. Specifically, the smaller value of β in Germany naturally leads to a larger child penalty because the household is behaving "as if" it places less weight on declines in income by the woman compared to the man following the child's arrival in the household.

Appendix Figures and Tables

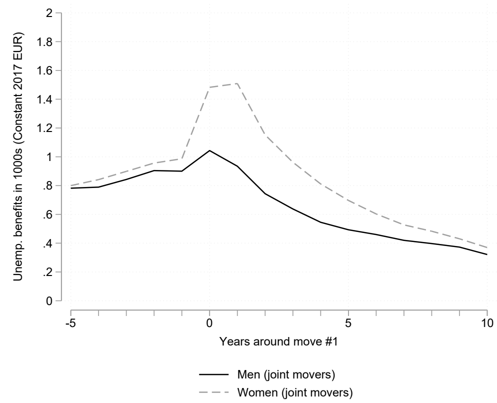
A.6 Other Employment Measures

Figure OA-1: Relationship between Moving and Other Employment Measures

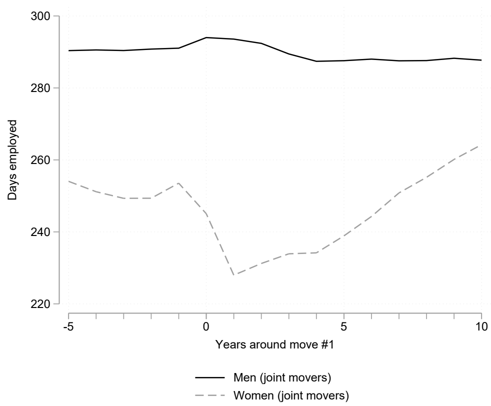
(a) Unemployment Benefits, Germany



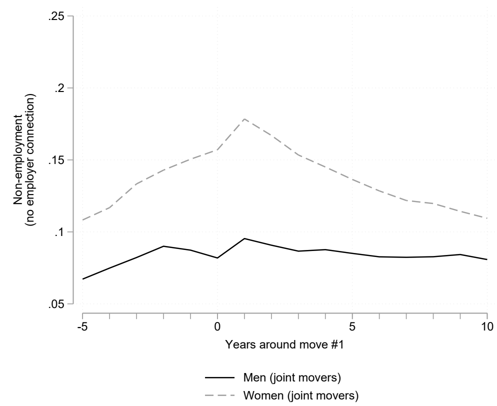
(b) Unemployment Benefits, Sweden



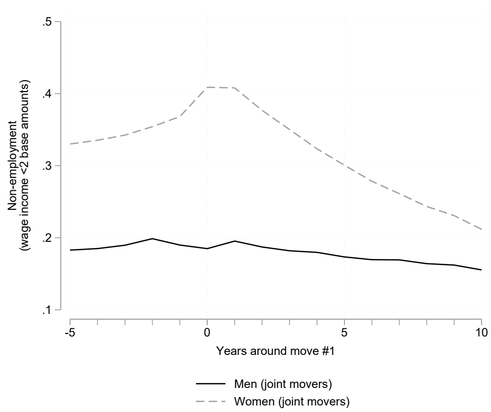
(c) Days Employed, Germany



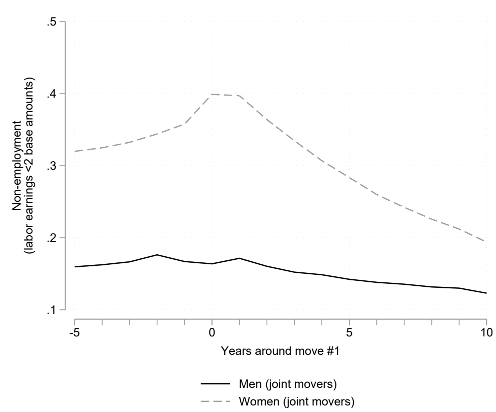
(d) No Employer Connection, Sweden



(e) Wage Income < 2 * Price Base Amounts, Sweden



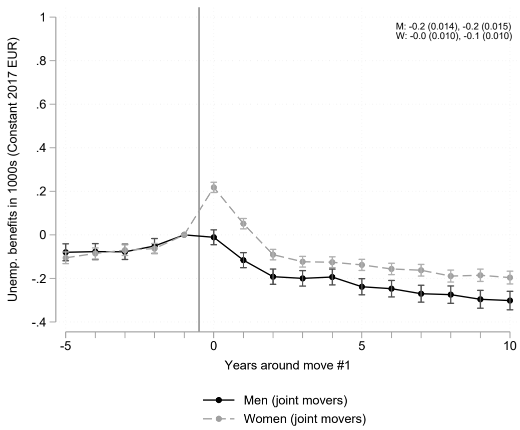
(f) Labor Earnings < 2 * Price Base Amounts, Sweden



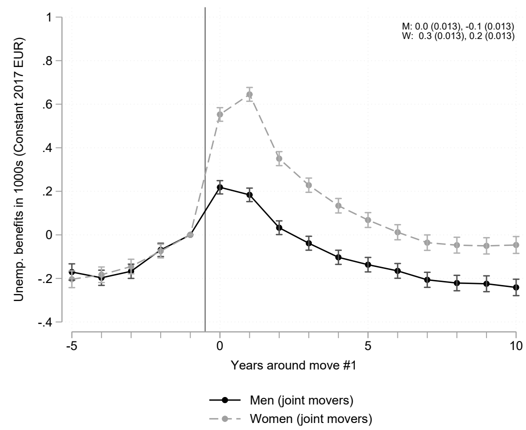
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first move, per gender.

Figure OA-2: Event Study Results on Other Measures of Employment

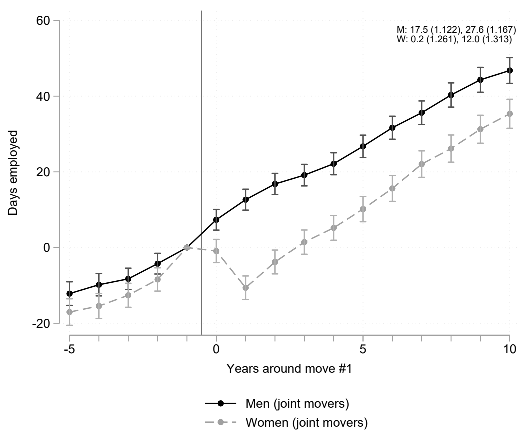
(a) Unemployment Benefits, Germany



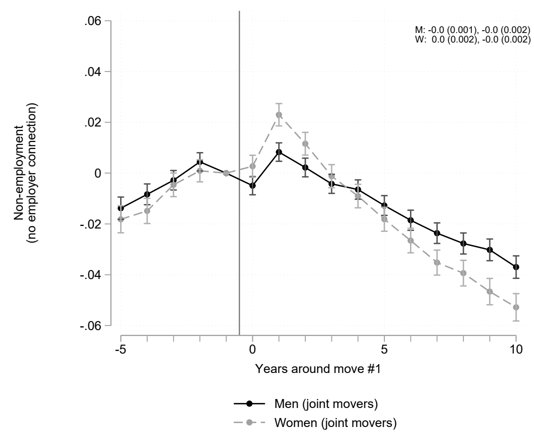
(b) Unemployment Benefits (Amount), Sweden



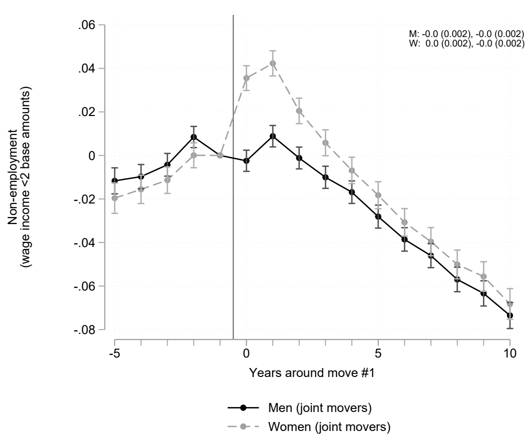
(c) Days Employed, Germany



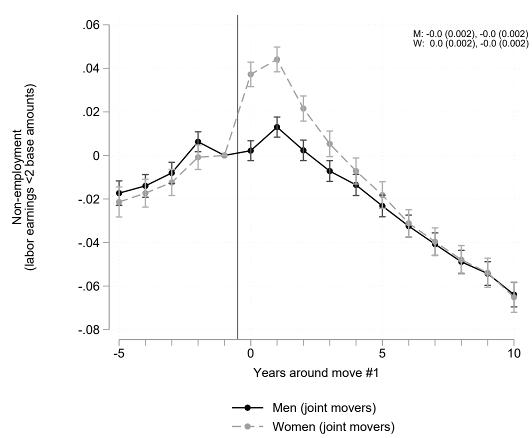
(d) No Employer Connection, Sweden



(e) Wage Income < 2 * Price Base Amounts



(f) Labor Earnings < 2 * Price Base Amounts, Sweden



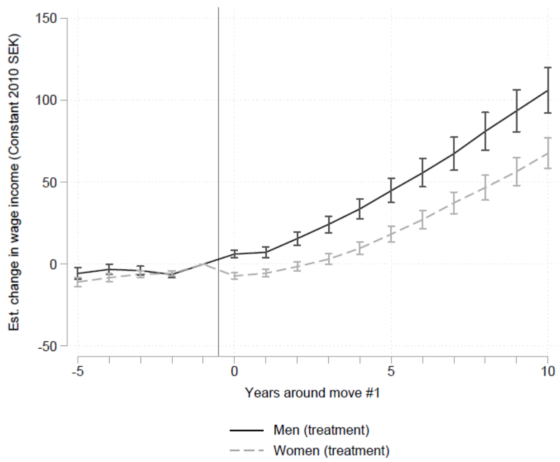
Notes: This figure displays the event study results that estimate the effect of moving on different outcomes in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W).

A.7 Heterogeneity

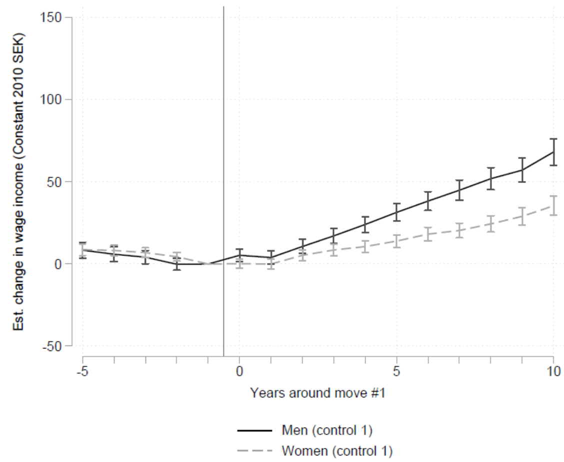
Figure OA-3: Impacts of Move on Wage Income - By Timing of First Joint Child, Sweden

Panel A

(a) First Child in $(t-3, t+3)$

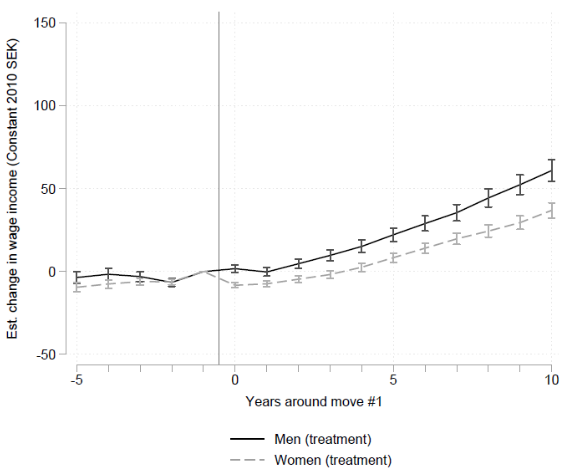


(b) No First Child Before $t+4$

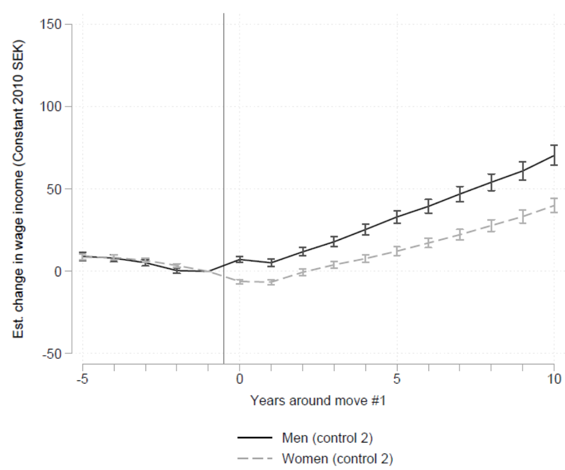


Panel B

(c) First Child in $(t-3, t+3)$



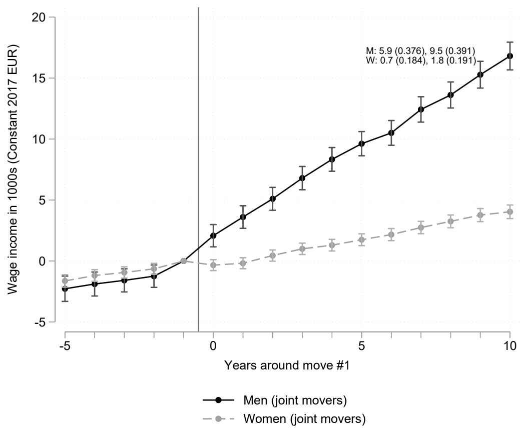
(d) No First Child in $(t-3, t+3)$



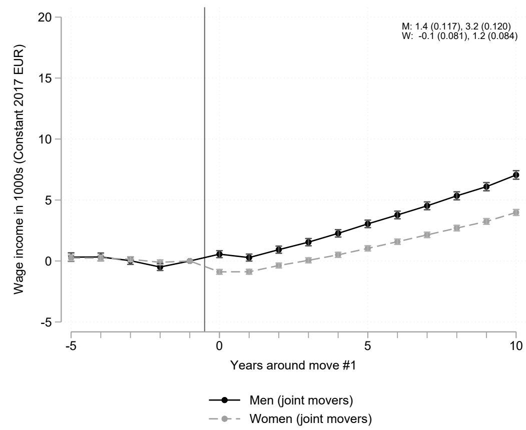
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move $(t-1)$ in Sweden. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The samples of figures (a), (b), and (d) have the following number of observations in $t=0$: 39,644; 19,720 (33% of the total observations); 56,440 (58% of the total observations). The sample for Figure (c) is the same as for (a). Note that the wage income in this figure is measured with different currency (2010 SEK).

Figure OA-4: Impact of Move on Wage Income – By Gender-specific Predicted Female Share of HH Income

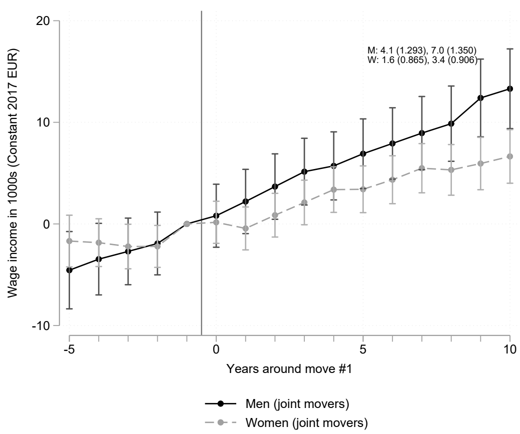
(a) Female Share of HH Income < 50%, Germany



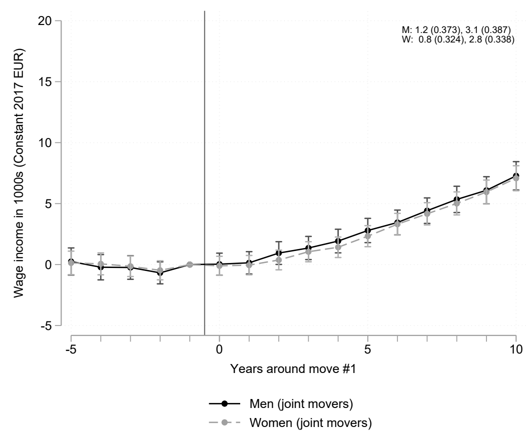
(b) Female Share of HH Income < 50%, Sweden



(c) Female Share of HH Income ≥ 50%, Germany



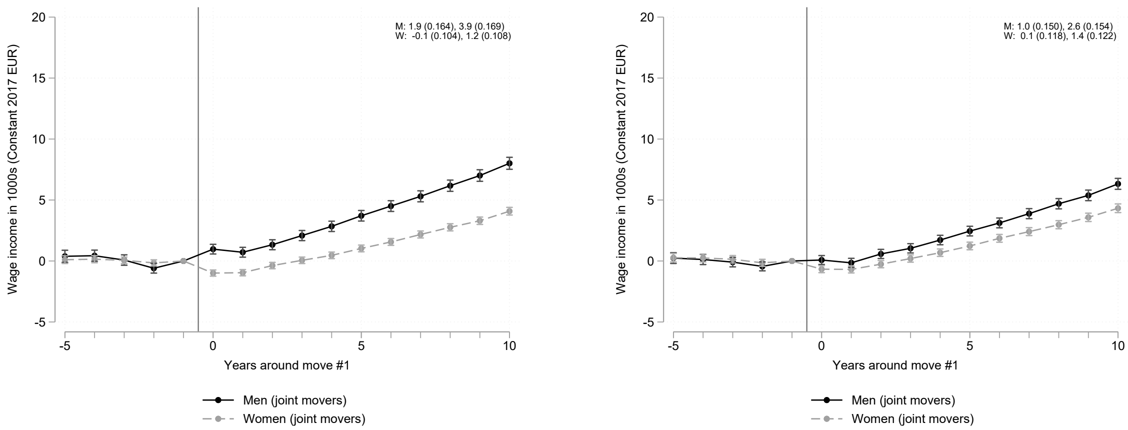
(d) Female Share of HH Income ≥ 50%, Sweden



Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move $(t-1)$. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t = 0$ to $t = 5$ and $t = 10$), in this order, for men (M) and women (W). Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old.

Figure OA-5: Impact of Move on Wage Income – By Predicted Female Share of HH Income, Median

(a) Female Share of HH Income < Median, Sweden (b) Female Share of HH Income $\geq$ Median, Sweden



Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W). Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. We do not have these results for Germany yet. The median female share of HH income is 48%.

A.8 Predicted Income Methodology and Results

We use the following earnings prediction model:

```
reghdfe lnwageinc i.expproxy, absorb(i.child18 i.lvlfield3 i.year, savefe), resid
```

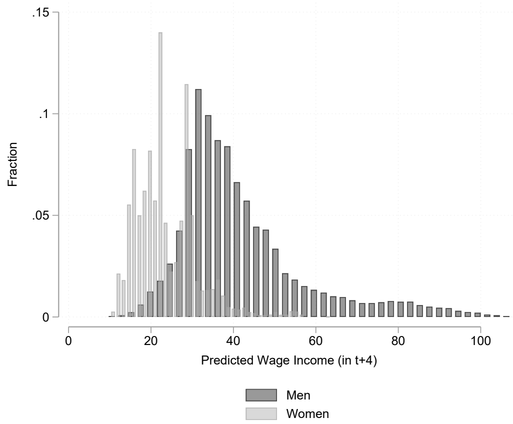
which controls for potential experience, number of children, college major (interacted with highest level of education), and year. In Germany, we do not have college major information so we replace with the highest level of education (three education categories: high school or less, vocational training, some college or more).

We estimate the model in both countries using a 1990-2017 panel with a sample of the population aged 25–54, dropping the individuals with a wage income below 2 price base amounts (which is our preferred proxy for non-employment), and we experimented with alternative models that included additional interactions between level of education.

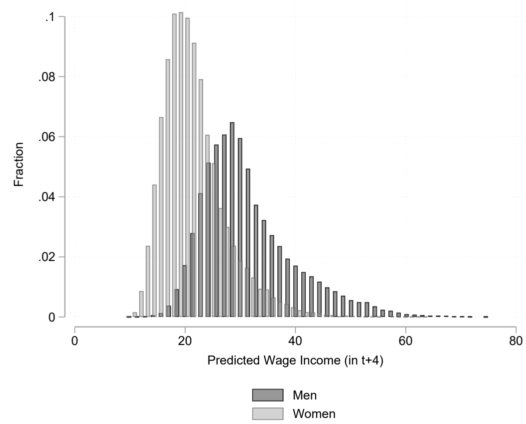
In the baseline analysis, we focus on *gender-blind* predictions so that the regression model above is run on men and women together. We also report results using *gender-specific* predictions where the regression model above is run on men and women separately.

Figure OA-6: Predicted Wage Income, Movers

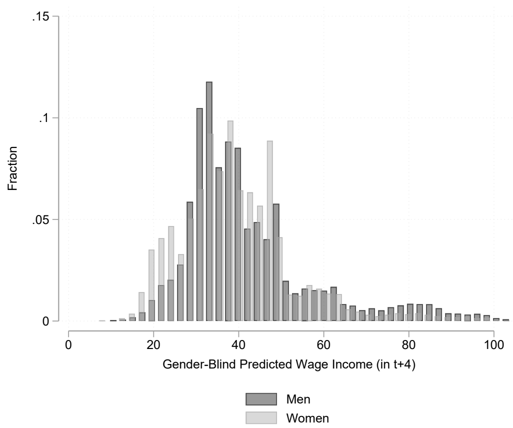
(a) Gender-specific, Germany



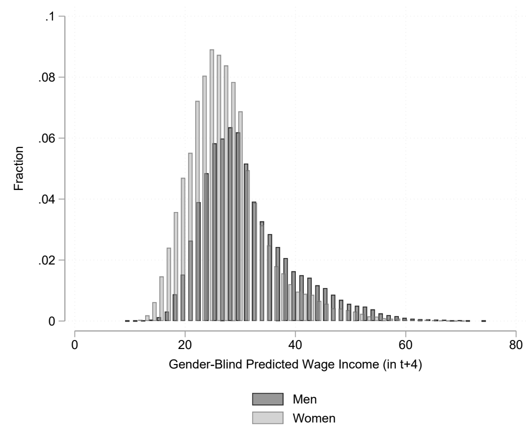
(b) Gender-specific, Sweden



(c) Gender-blind, Germany



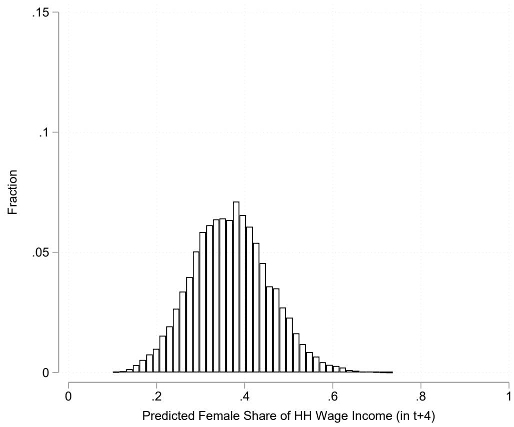
(d) Gender-blind, Sweden



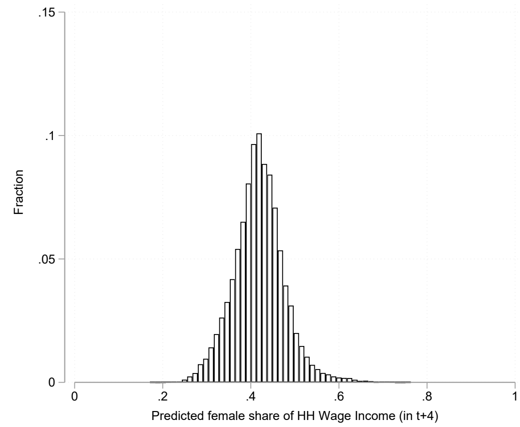
Notes: This figure displays histograms of predicted wage income by gender for each country on the movers sample. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. Gender-blind predicted earnings are calculated by regressing men's log individual income on experience indicators and education level interacted with field of study, in a way that men and women with the same covariates have the same predicted wage income.

Figure OA-7: Predicted Female Share of HH Income, Movers

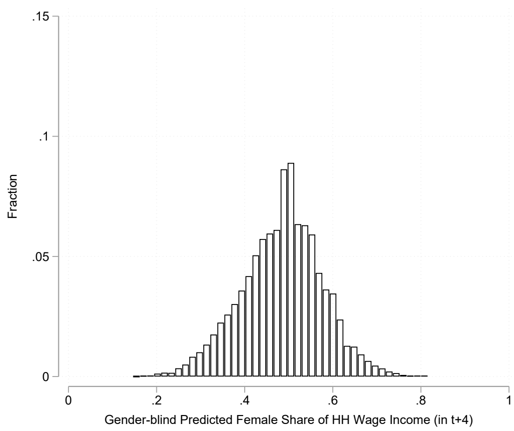
(a) Gender-specific, Germany



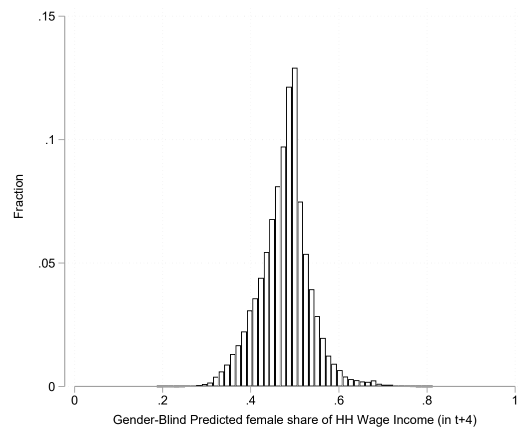
(b) Gender-specific, Sweden



(c) Gender-blind, Germany



(d) Gender-blind, Sweden

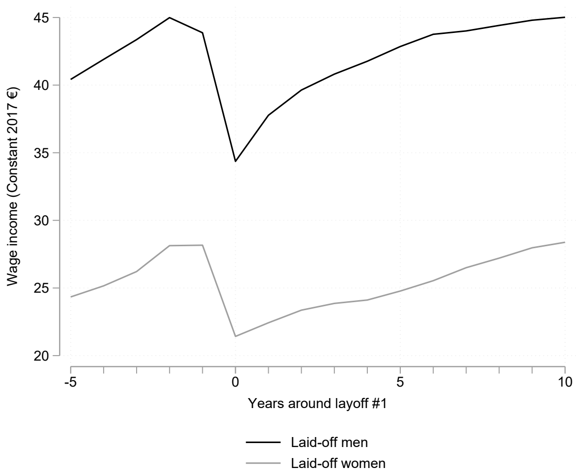


Notes: This figure displays histograms of predicted female share of household income by country on the movers sample. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. Gender-blind predicted earnings are calculated regressing men's log individual income on experience indicators and education level interacted with field of study, in a way that men and women with the same covariates have the same predicted wage income.

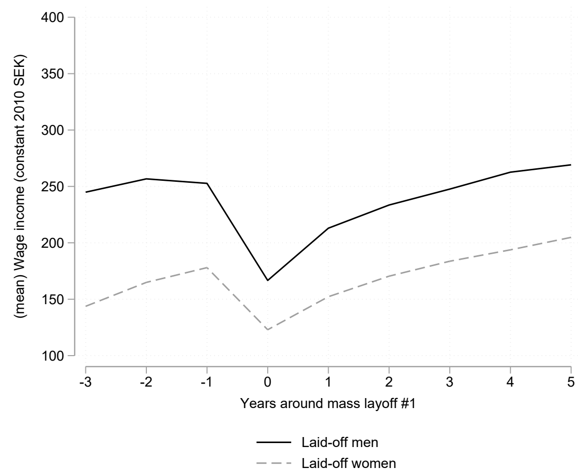
A.9 Descriptive figures for layoffs

Figure OA-8: Relationship between Layoffs and Labor Earnings and Employment

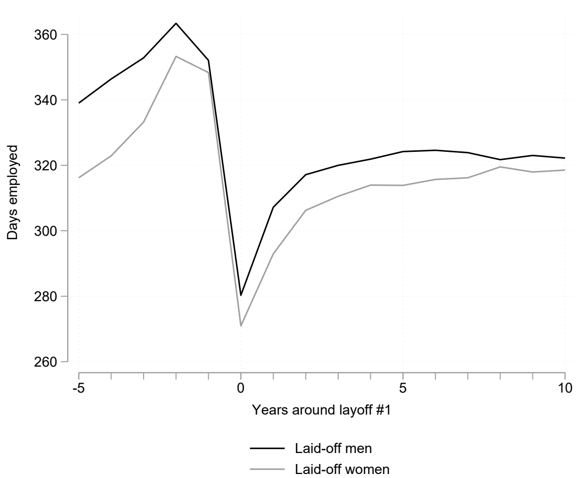
(a) Wage Income, Germany



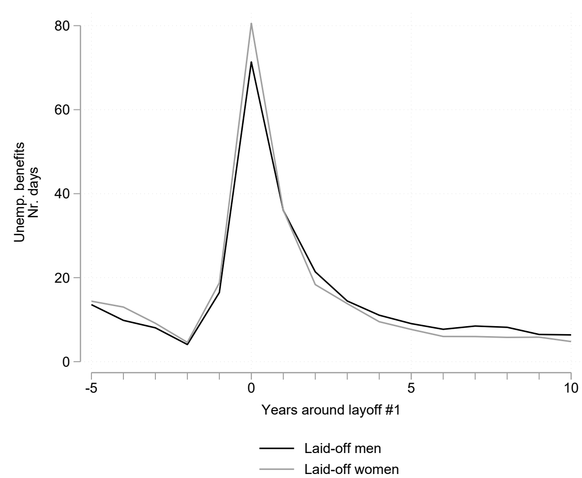
(b) Wage Income, Sweden



(c) Days Employed, Germany



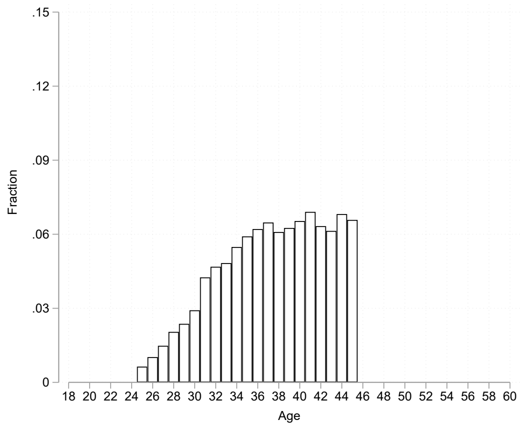
(d) Days UI Benefits , Germany



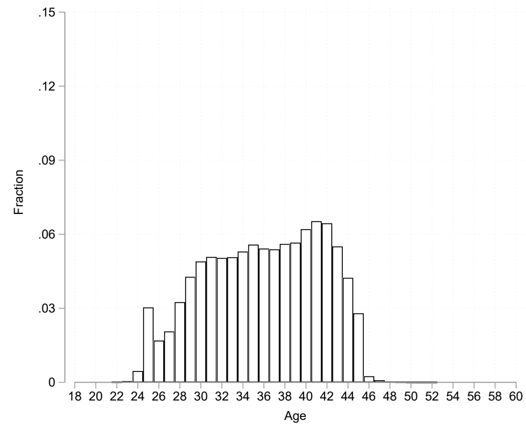
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first layoff event, per gender.

Figure OA-9: Age Distribution for Laid-off Individuals, Sweden

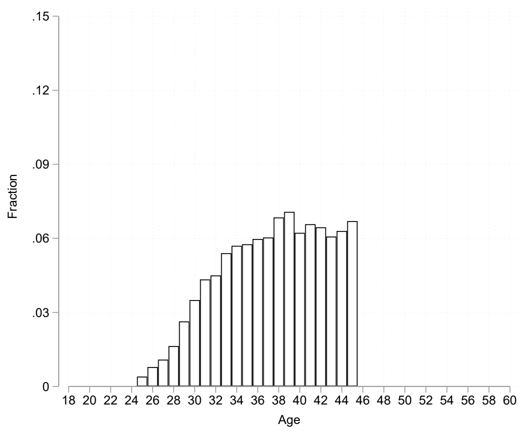
(a) True Layoffs, Women



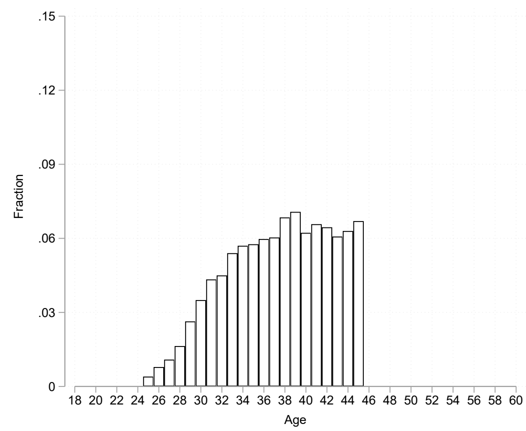
(b) Placebo Layoffs, Women



(c) True Layoffs, Men



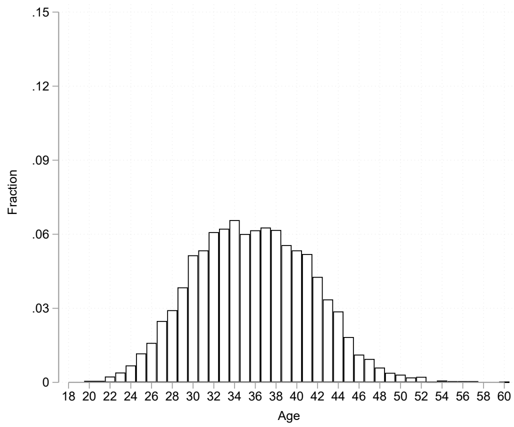
(d) Placebo Layoffs, Men



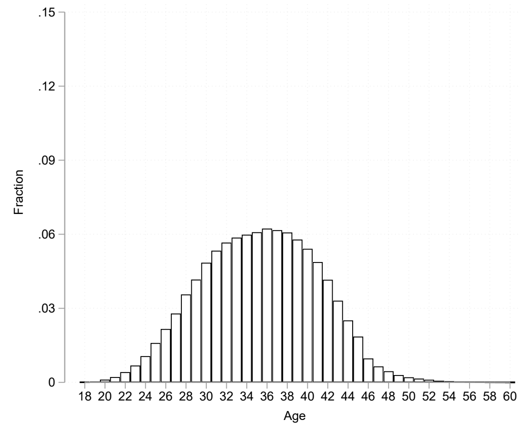
Notes: This figure displays histograms of age by gender for the laid-off individuals sample in Sweden.

Figure OA-10: Age Distribution for Partners of Laid-off Individuals, Sweden

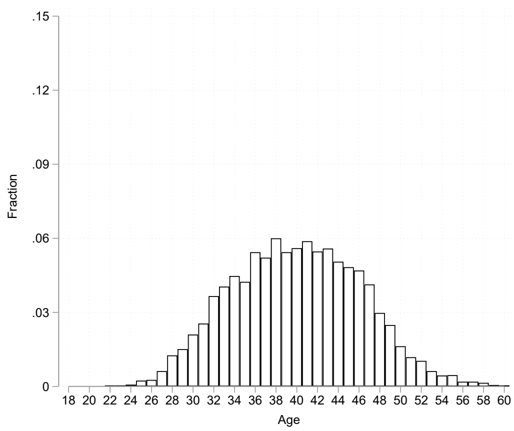
(a) True Layoffs, Female Partners



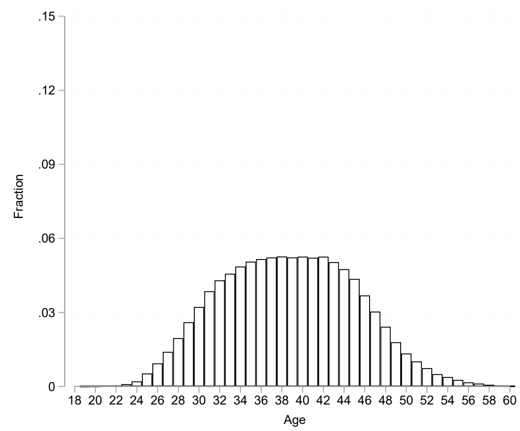
(b) Placebo Layoffs, Female Partners



(c) True Layoffs, Male Partners



(d) Placebo Layoffs, Male Partners



Notes: This figure displays histograms of age by gender for the partners of laid-off individuals sample in Sweden.

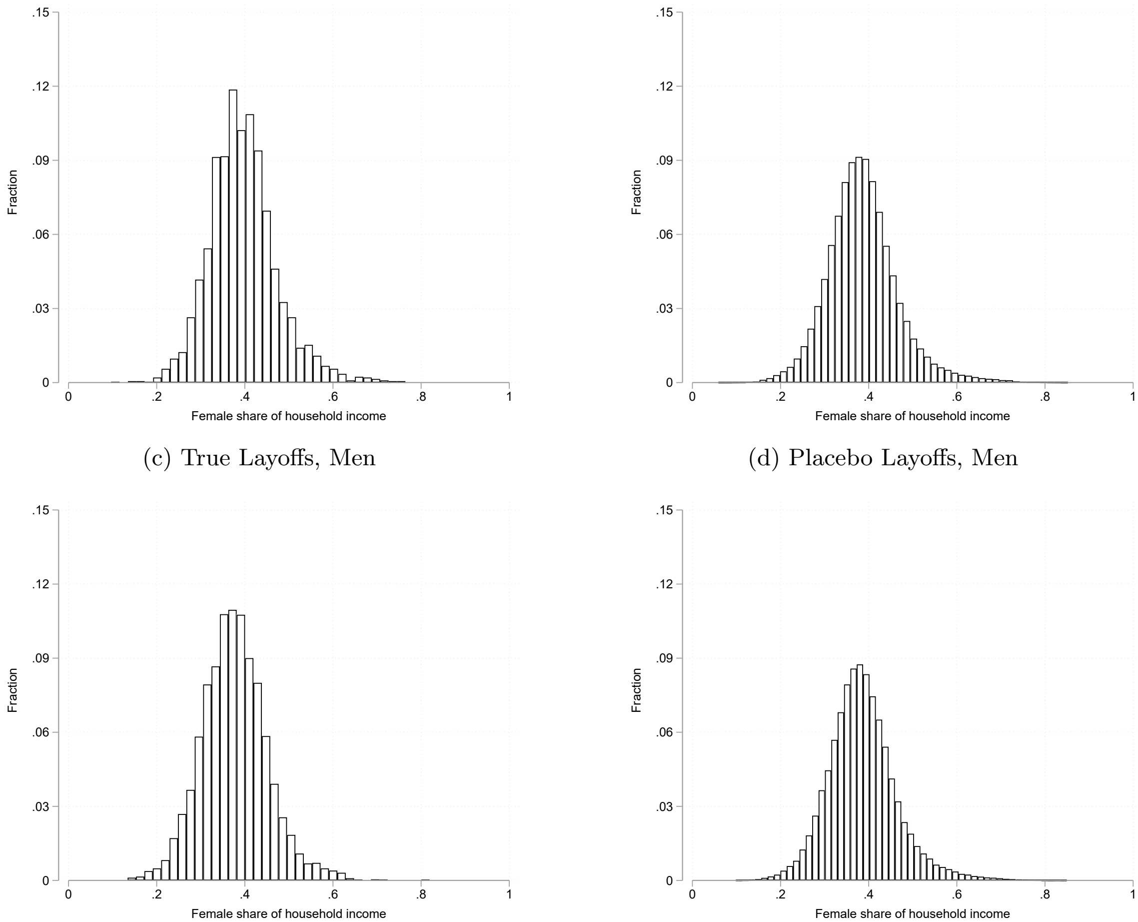
Figure OA-11: Predicted Female Share of HH Income for Laid-off Individuals, Sweden

(a) True Layoffs, Women

(b) Placebo Layoffs, Women

(c) True Layoffs, Men

(d) Placebo Layoffs, Men

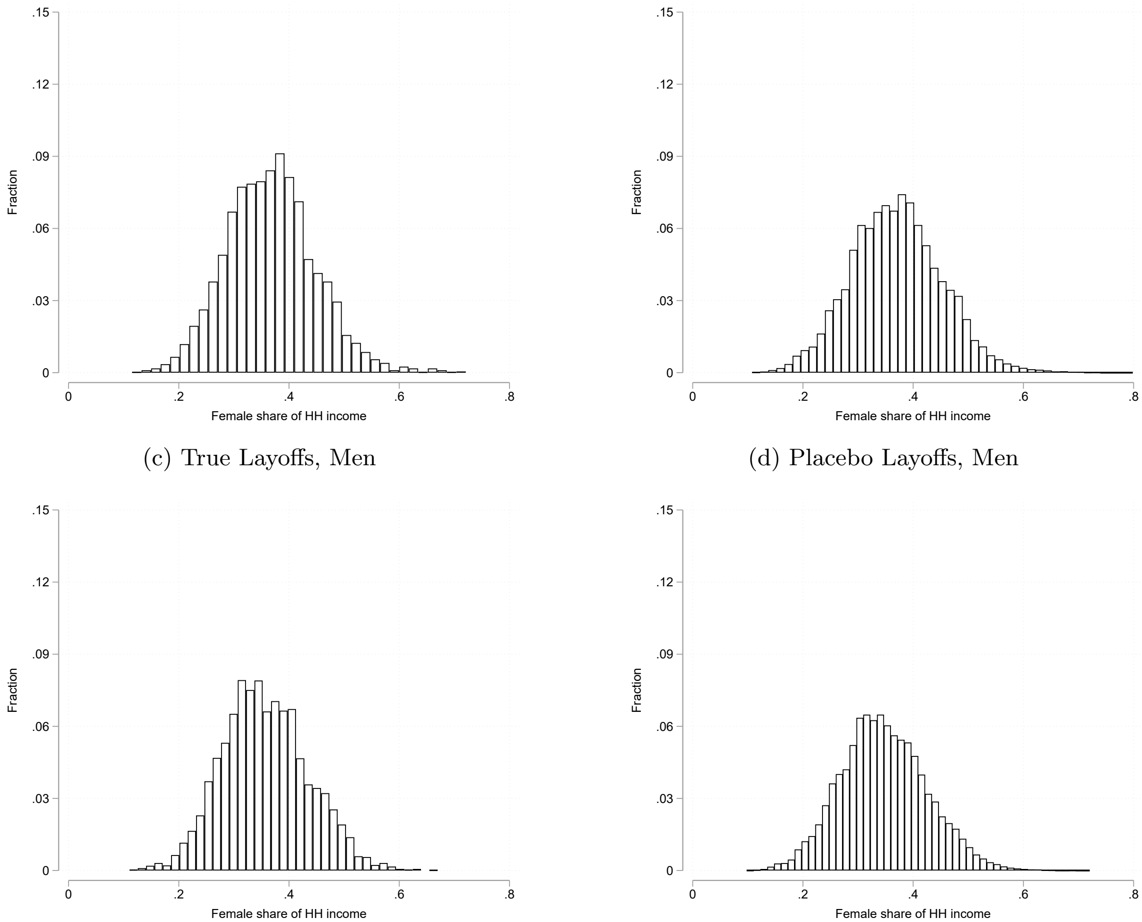


Notes: This figure displays histograms of predicted female share of household wage income by gender for the laid-off individuals sample in Sweden in $t = 4$. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old.

Figure OA-12: Predicted Female Share of HH Income for Laid-off Individuals, Germany

(a) True Layoffs, Women (b) Placebo Layoffs, Women

(c) True Layoffs, Men (d) Placebo Layoffs, Men



Notes: This figure displays histograms of predicted female share of household wage income by gender for the laid-off individuals sample in Germany in $t = 4$. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old.

Table OA-1: Stepwise Restrictions to Layoffs Sample, Sweden

Sample Nr	Sample restriction	# workplace IDs	# employees
0	Workplace restrictions only (including non-laid off individuals)	1,147	151,150
1	Excl. people staying at $t-1$ workplace	1,147	104,486
2	Balanced sample (in LISA $t-3$ to $t+5$)	1,147	98,473
3	Age restriction 18-65	1,147	97,022
4	Only including 1st layoff	1,147	97,022
5	Excl. ind. working at $t-1$ workplace in $t=1/5$	1,147	93,436
6	Requiring tenure $(t-2/t-1)$	1,147	68,693
7	Requiring labor market attachment (wage income >2 pba in $t-1$)	1,145	57,945
8a	Keeping only married/cohabiting couples	1,117	32,159
8b	8a + w/ unemployment benefits in t	721	3,465
9a	Keeping only marrieds/cohabs, ages 25-45	1,087	16,164
9b	9a + w/ unemployment benefits in t	584	1,996

Notes: This table displays the number of observations for each step in the restrictions applied to the layoffs sample in Sweden.