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, including those not used to estimate the model.

JEL classification: J61, J16, R23

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

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1 Introduction

Over the past half 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 match 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). If couples adhere to traditional gender norms, location decisions may systematically be made to benefit the man's career even if the woman has higher earnings potential.

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. We employ two designs to test whether moves disproportionately help men or women within a couple. First, we use an event study design to 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 (with 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. The gender gap in

[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).

earnings following a move is present across all age groups but 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. Controlling for child birth events and comparing couples who do and do not have children around the time of the move show that the earnings gap is not driven by couples deciding to have a child around the time of a move.

Second, we use mass layoff events to study whether couples are more likely to move when the man is laid off as opposed to the woman. Mass layoffs generate plausibly exogenous job separations for both men and women in our sample of couples and job displacement induced long-distance moves (Huttunen et al. 2018). 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 collective 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. In Sweden, the gender gap closes completely among couples in which women have higher potential earnings, but in Germany we find that men still benefit more than women following a move, even with the women have higher potential earnings. In both countries, these results are difficult to reconcile with a standard collective model because women are expected to benefit more than men from moving when they have higher potential earnings.

With these empirical results as motivation, we structurally estimate the model parameters separately for each country. We test (and reject) a collective model of decision-making in both countries, with larger deviations from the collective 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 estimation.

Our reduced-form results use a relatively standard event-study framework as well as mass layoff events to generate 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 who currently reside in a different commuting zone, 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.

We interpret our model as suggesting that a gender norm of prioritizing men's careers leads couples to leave money on the table, but it could also be that couples are rationally anticipating that the woman will soon leave the labor market, for example, after the birth of a child. Therefore, even if a woman currently has higher earnings potential than a man, the couple may anticipate her earnings being substantially lower in the future. We therefore provide two additional pieces of evidence to argue that the results are due to a gender norm. First, we compare the earnings gap between couples who do not have a child in our sample period and those who do, finding that the gap is only slightly smaller among couples that do not have a child. Second, we compare couples who are of East or West German origin. Prior work has shown that women with East German origins are more likely to work and return to work more quickly following the birth of a child (Rosenfeld et al. 2004; Boelmann et al. 2021). Consistent with this literature, we find that the gender gap in earnings is largest among couples in which neither spouse is of East German origin and smaller among couples in which at least one spouse is of East German origin. The gap disappears among couples in which the man's is grown up in East Germany.

Overall, we argue that our empirical results and model-based estimates suggest that a gender norm that prioritizes men's career advancement over women's accounts for a significant portion of the gender earnings gap that emerges following a move.

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 a 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 provides additional evidence that a gender norm explains the results, and in Section 7 we explore alternative mechanisms. Section 8 concludes.

2 Data

We use administrative data from Sweden and Germany to test whether, within heterosexual couples, moves disproportionately benefit men. These datasets are very valuable for four 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, which we can use as an exogenous negative labor market shock that could lead to a move. And, finally, the data allow for much larger samples than longitudinal surveys.

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) with the couple identifier generated by Baechmann et al. (2021).[2] The IEB includes all employees subject to social security (this excludes civil servants and self-employed), everyone receiving 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 in the same location (geocoded buildings), have a matching last name (at least one part in case of double names), be of different sexes, have an age

[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.

difference of less than 15 years, and live in buildings with no other people with the same name with records in the data. The identification of couples is done every year on June 30 from 2001 to 2014 which implies that in a particular year couples can only identified as a couple if both spouses have a record in the IEB for that particular date. This is the case if they are (marginally) employed or unemployed.[3]

According to the analysis in Goldschmidt et al. (2017) the algorithm produces only few false positives. Quantitatively much more important are married couples not identified: only about one third of married couples living in Germany and attached to the labor market are found (Goldschmidt et al. 2017). The main reason is that for a large number of individuals in the IEB no exact geocodes are assigned (Baechmann et al. 2021). In addition, the algorithm identifies fewer couples living in large buildings and it misses out those with different names. Married couples with no common name are likely to be less conservative on average, although sharing a common name is still very widespread: for those couples who married in 1996 (2016) 91% (87%) share a common name according to the Society of the German language (GFDS 2018). There exists no other way of linking family members in German administrative employment data. For this reason, we also have no chance to identify non-married couples or singles.

The IEB data includes employment spells with information on earnings, occupation, and other job details spanning from 1975 to 2021. The earnings information is very accurate, as the employer has to report earnings for social security purposes. However, German administrative data only includes wages up to the social security contribution ceiling and we hence impute right-censored wages.[4] In addition, the IEB includes every period of receiving unemployment benefits together with the amount of benefits, as well as information on periods of job search and participation in subsidized employment and training programs. In addition, the data include personal characteristics like year of birth and education. The data providing institute can link employment spells to establishments and from these links variables indicating mass layoffs have been created.[5]

2.2 Swedish Data

[3]This 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.

[4]For this imputation and other steps of data preparation we follow the suggestions in Dauth and Eppelsheimer (2020). For the identification of children through maternity leave spells, we follow Müller and Strauch (2017).

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

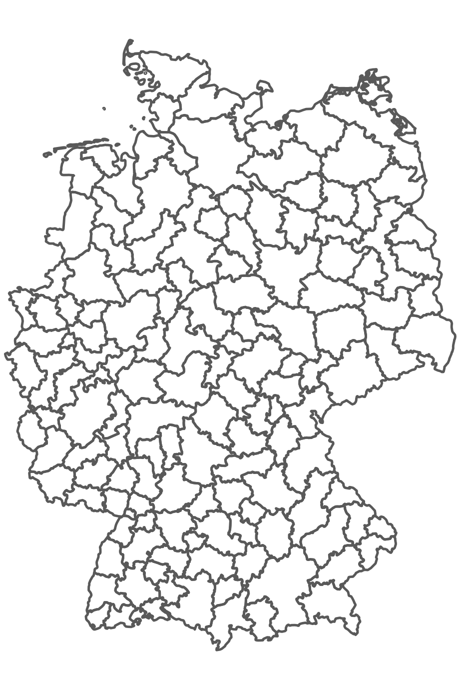
We use individual-level administrative data from Sweden from the GEO-Sweden database. The database covers the entire Swedish population of 10 million people, whom we can track over time starting in 1990. In addition, we can identify the building in which individuals reside, allowing us to identify couples. 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.

2.3 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[6] (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. We therefore allow for the possibility that one spouse moves in year t while the other follows in year $t+1$.

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

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).

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 in 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 firm-based education (e.g. apprentice, intern) in the five years before a move. We have no information on college enrollment.[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 $22,556$ moving couples in Germany and $44,499$ couples in Sweden.

2.4.2 Layoff Sample

For this analysis we consider displacements from mass layoffs between 2001 and 2006. In the German data a mass layoff is defined as an establishment with at least 50 employees experiencing a decline of more than 30%.[9] Our sample consists of those workers experiencing a mass layoff who had at least one year of tenure and have not been laid of before.[10]

2.4.3 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. Information on hours worked is not available. For non-working spouses, the wage income is set to zero.

Table 1 presents descriptive statistics for our two samples. The average age of couples in similar in each sample. Education levels are different 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[11]. 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] The definition also requires that the establishment had no increase of more than 30% of employees in the two preceding years and no more than 20% of the outflow is going to one particular establishment. This definition is similar to Schmieder et al. (2023) and other papers using German data.

[10] Further restrictions are 1) the couple is already identified as a couple before the layoff, 2) the worker does not return to the establishment in the five subsequent year, 3) in the rare case in which both partners are laid off at the same time the couple is not used for the analysis.

[11] 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	Women	Men	Women
	(1)	(2)	(3)	(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	0.62	0.62	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	20566	20566	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. In the German data we measure completed college instead of some college.

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	0.11	0.08	0.15	0.09
	(0.09)	(0.15)	(0.08)	(0.10)	(0.31)	(0.28)	(0.36)	(0.29)
High school	0.09	0.09	0.06	0.09	0.55	0.53	0.54	0.55
	(0.28)	(0.28)	(0.23)	(0.29)	(0.50)	(0.50)	(0.50)	(0.50)
Vocational training	0.76	0.79	0.78	0.79	0.12	0.03	0.06	0.04
	(0.43)	(0.41)	(0.41)	(0.41)	(0.32)	(0.18)	(0.24)	(0.20)
Some college	0.14	0.10	0.15	0.11	0.06	0.15	0.06	0.11
	(0.35)	(0.30)	(0.36)	(0.31)	(0.23)	(0.36)	(0.25)	(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	0.44	0.73	0.54	0.47
	(1.61)	(1.19)	(1.70)	(1.21)	(1.72)	(2.16)	(2.16)	(1.64)
Days receiving UI benefits (per year)	16.47	18.60	16.16	18.77	11.49	15.32	11.88	9.86
	(41.26)	(70.34)	(59.97)	(46.28)	(39.25)	(48.20)	(46.87)	(35.75)
At least 1 child	0.57	0.57	0.47	0.47	0.91	0.92	0.89	0.90
	(0.49)	(0.49)	(0.50)	(0.50)	(0.28)	(0.28)	(0.31)	(0.31)
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	8052	8052	6768	6768

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. In the German data we measure completed college instead of some college.

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. We control for the individual's potential experience and education level, as well as calendar year, treating the timing of the move as exogenous. The identification assumptions for an event study design are no anticipation, so that the timing is exogenous, and parallel trends so that any post-move changes can be ascribed to the move. In our setting, analogous to the child penalty setting, the existence of the event is not exogenous to the couple: They choose to move. Moreover, they likely do so in response to employment shocks (e.g., better job opportunities elsewhere), so anticipated effects of the event on the outcome (earnings) might prompt the event. 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. Our research question, in fact, leans on these anticipated effects: Are couples as likely to move for anticipated increases to the woman's earnings as to the man's?

One 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 also control for child event-time indicators. Another threat is if women have fewer better job opportunities elsewhere than men do. In the event study design, we are not directly observing the employment shocks; we assume they are the same and observe the response. We address this in Section 7 by re-weighting men and women to have the same occupational distribution, among other robustness checks.

Our main estimation equation is

$$\begin{aligned} Y_{ist}^{g} = &\sum_{j \neq -1} \alpha_j^g \times \mathbb{1}[j = t] + \sum_k \beta_k^g \times \mathbb{1}[k = \mathrm{e\hat{x}p} + \sum_p \gamma_p^g \times \mathbb{1}[p = \mathrm{educ}_{is}] \\ &+ \sum_y \nu_y^g \times \mathbb{1}[y = s] + \sum_m \tau_m^g \times \mathbb{1}[m = t_{ch}] + \theta_n^p \times \mathbb{X} + \epsilon_{ist}^g \end{aligned} \tag{1}$$

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 ($m = t_{ch}$).[12] Standard errors are clustered at the individual level.

[12]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.

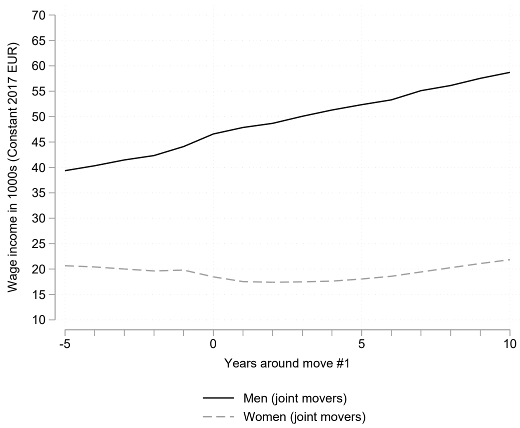
To investigate whether spouses' earnings responses are driven by changes in employment or in wages, panels (c) and (d) of Figure 3 and (a)-(f) of Figure OA-2 show the effects of a move on various employment measures of men and women. In Germany, the number of days a person is employed increases by 20 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).[13] 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.

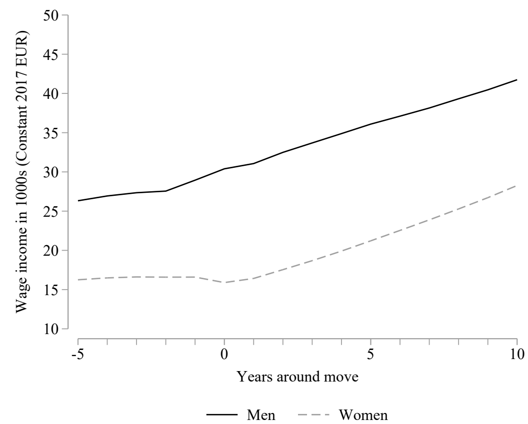
[13]This normalization follows the approach in the recent "child penalty" literature (see, e.g., Kleven et al. 2019a).

Figure 2: Relationship between Moving and Labor Earnings and Employment

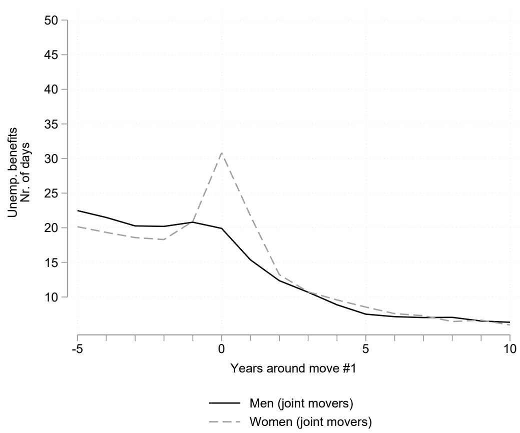
(a) Wage Income, Germany



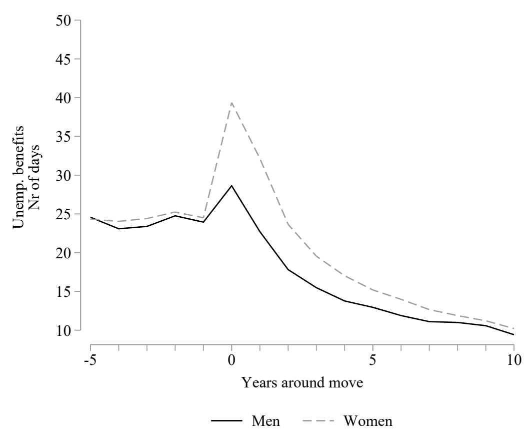
(b) Wage Income, Sweden



(c) Days Unemployment Benefits, Germany

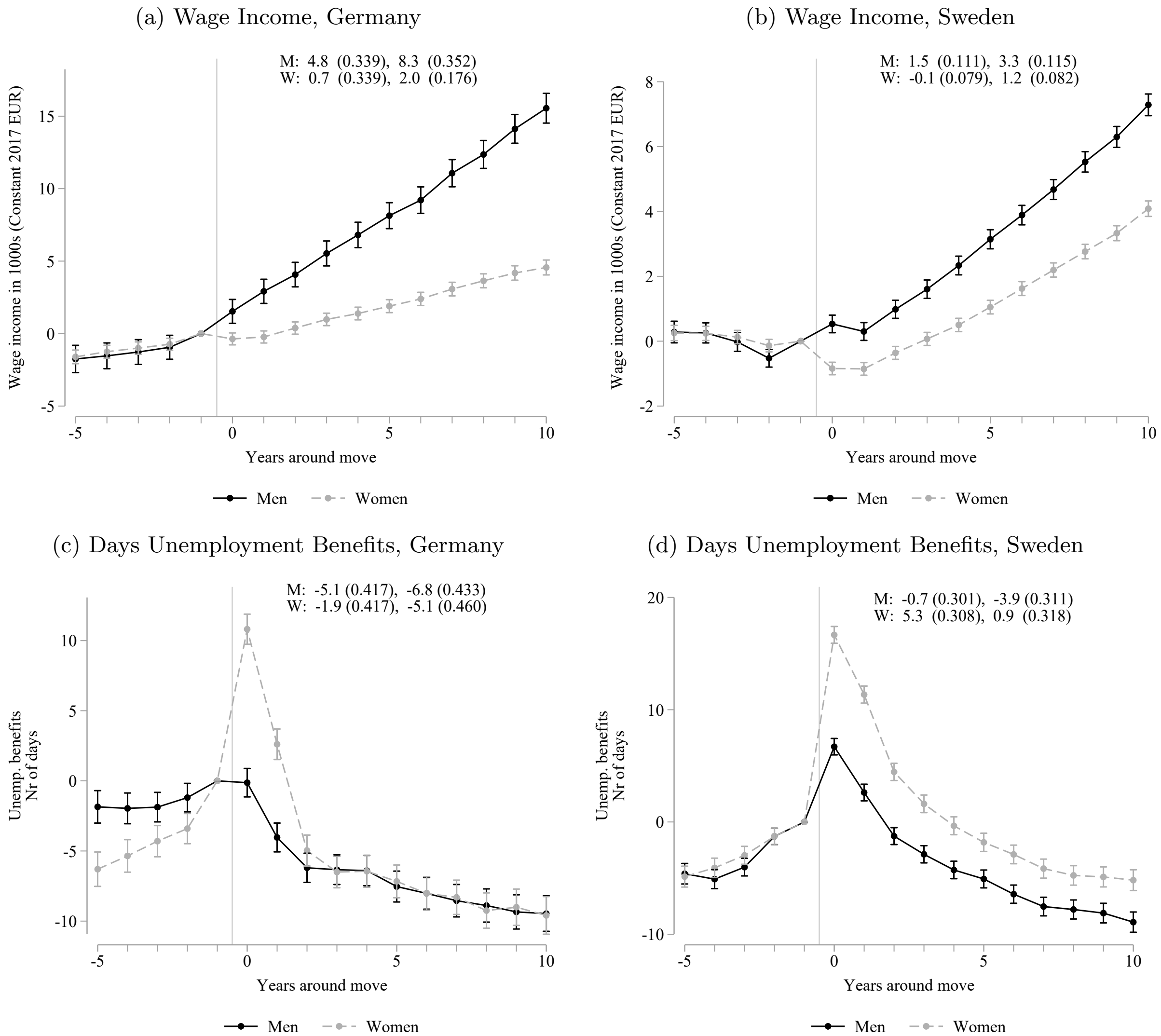


(d) Days Unemployment Benefits, Sweden



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

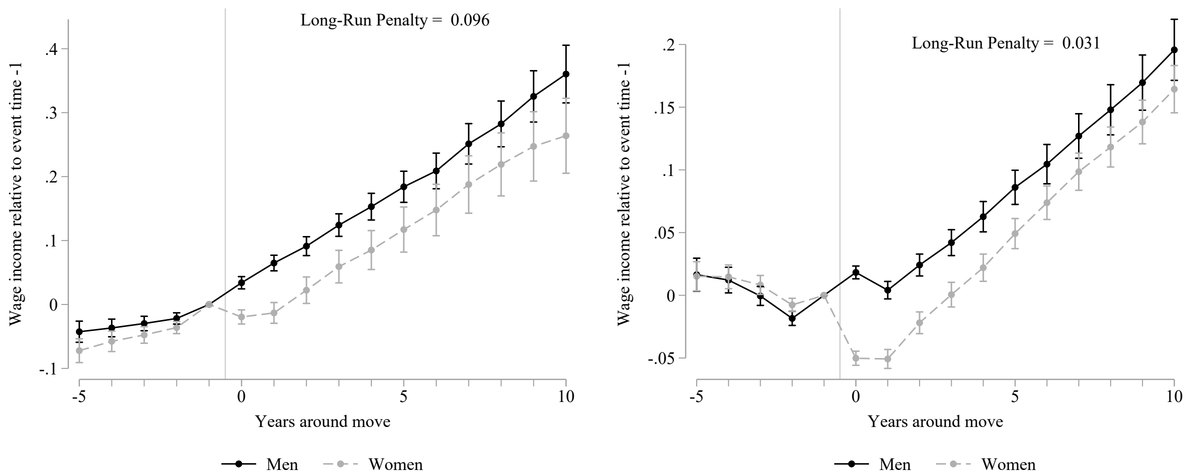
Figure 3: Impact of Move on Labor Earnings and Employment



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

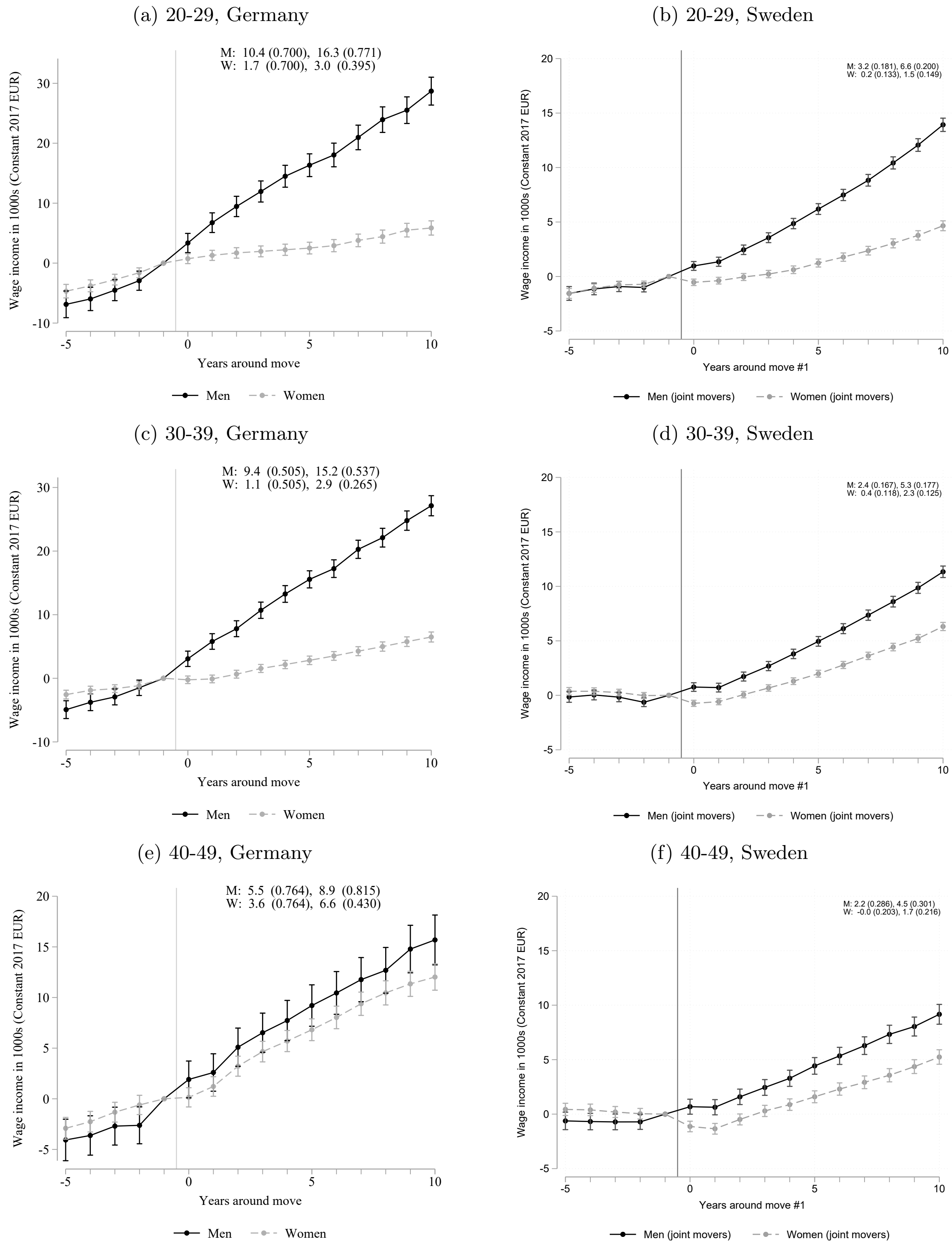
(a) Germany (b) Sweden



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 $t = 10$.

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



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).

4.3 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.[14] 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).

Our event study and mass layoff results both suggest that, within heterosexual couples, moves tend to benefit men. Several mechanisms could explain our results. First, the gender gap that emerges after moving, and the difference in willingness to move following a layoff, could be due to women having lower earnings or lower earnings potential than men. It could also be that, even if women's earnings are not currently lower than men's, couples anticipate that women will leave the labor force after having a child, resulting in lower future earnings. Women may work in occupations with lower returns to moving. All of these explanations suggest that couples are behaving rationally and maximizing household earnings. An alternative explanation is that couples face gender norms that compel them to prioritize the man's

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

career over the woman's career. In the next section, we attempt to distinguish between men having higher potential earnings and a gender norm that prioritizes men's career advancement, arguing that the results are in part driven by the latter. We then provide additional evidence that norms drive our results, and return to alternative explanations, including anticipating a "child penalty" and selection into occupations.

Table 3: Impact of Layoffs on Moving Probability

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Layoff Men	0.00680***	0.00581***	0.00594***	0.0147***	0.0148***	0.0146***
	(0.00147)	(0.00149)	(0.00148)	(0.00190)	(0.00189)	(0.00189)
Layoff Women	0.00127	0.00149	0.00174	-0.00294**	-0.000448	-0.000577
	(0.00143)	(0.00143)	(0.00144)	(0.00133)	(0.00133)	(0.00134)
Age FE		✓	✓		✓	✓
CZ FE			✓			✓
# Layoff Men	6828	6828	6828	8052	8052	8052
# Layoff Women	4458	4458	4458	6768	6768	6768
Mean	0.00719	0.00719	0.00719	0.0146	0.0146	0.0146
M=W p-value	0.041	0.191	0.146	<0.001	<0.001	<0.001
Observations	165449	165449	165449	263680	263680	263680

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 purpose of our model is to distinguish between two main explanations for our results: (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 do so, we model household migration decisions by extending a standard model of collective decision-making, in which couples maximize household income, to allow them 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 collective model with gender differences in potential earnings.[15]

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 collective 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 and compare the simulated effects to the estimated effects of job layoffs documented above, and we also use the model to simulate the earnings effects of childbirth and compare the simulated effects to existing empirical estimates of 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: $\log(y_{i1}) \sim N(\mu_i, \sigma^2)$.[16] With this setup, the average gender gap in period 1 is $E[y_{M1}] - E[y_{F1}] = \exp(\mu_M + \sigma^2/2) - \exp(\mu_F + \sigma^2/2)$. We define $s = y_{F1}/(y_{M1} + y_{F1})$ to be the female's share of total household income in period 1.

[15] 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 the propositions and simulations in the Appendix 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.

[16] 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 Appendix and show in simulations that our main propositions go through with both of these extensions.

Migration decision. For simplicity, we assume that each household member receives the same income in period 2 as they received in period 1 if the household chooses not to move. Each household member independently draws a potential income in period 2 that they would receive if they choose to move move, with potential income $y_{i2} = (1 + \varepsilon_{i2})y_{i1}$ 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. We assume that a **collective 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. We define the change in income for each household member as $\Delta y_i = y_{i2} - y_{i1}$. With this setup, a collective household moves if and only if $\Delta y_M + \Delta y_F > c$. A **non-collective household** places a different weight on the female's income compared to the male's income, given by a relative weight parameter β; this type of household will move if and only if $\Delta y_M + \beta \Delta y_F > c$. If $0 < \beta < 1$, then the household places less weight on the female's income compared to the male's income. If $\beta = 1$, then the household behaves as a collective household.

The following proposition describes the average change in income from moving (conditional on moving) in the full population:

Proposition 1 *If $\mu_M > \mu_F$ and all households are collective households, then the average change in income from 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 (because $\mu_M > \mu_F$ implies $E[y_{M1}] - E[y_{F1}] > 0$) and the distribution of the potential returns to migration is the same for both genders, then in collective 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 collective model and do not necessarily imply any inefficiency in household decision-making.

The full proof is given in the Appendix and uses the fact that the distribution of the female share of household income in period 1 follows a logit-normal distribution.[17] Some intuition can be gained from the following lemma:

Lemma 1 *If* $\mu_M > \mu_F$ *and all households are collective 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. In the Appendix, we prove that if $\mu_M > \mu_F$, then $E[s] < 0.5$ in the population.[18] Thus, since the average household has $s < 0.5$ and all households with $0 < s < 0.5$ have expected return to moving larger for men then women, then it stands to reason that integrating across all households in the population will lead to an unconditional average return that is larger for men than women in the full population; this is the formal statement in Proposition 1.

While Proposition 1 shows that it is not possible to rule out a collective 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 when all households are collective households:

Proposition 2 *If* $\mu_M > \mu_F$ *and all households are collective households, then the average change in income from 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 collective 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.

[17] A logit-normal distribution is defined by a random variable whose logit has a normal distribution. Take the female share s and define x as the logit transformation $x = \log(s/(1-s))$. Since $s = y_{F1}/(y_{F1} + y_{M1})$, then $x = \log(y_{F1}) - \log(yM1)$. Since y_{F1} and y_{M1} are independent log-normally distributed random variables, then x is a normally distributed random variable, which implies that s is distributed according to the logit-normal distribution.

[18] While there are no closed-form expressions for any of the moments of a logit-normal distribution, a careful inspection of our proof reveals that we can still bound the mean of s with knowledge of the relative magnitudes of μ_M and μ_F.

Propositions 1 and 2 are both established in a 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-collective households, where households behave "as if" they put different weight on income earned by the woman relative to income earned by the man. We focus on the case where the households put less weight income earned by the woman, so that $0 < \beta < 1$ (with $\beta = 1$ corresponding to the collective household benchmark). In contrast to Proposition 2, when households are non-collective 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-collective households with $0 < \beta < 1$, then the average change in income from 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 collective household model is that we should be able to find households with similar permanent 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 collective model and conclude that households instead 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 collective 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 collective 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 Earnings Gap 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 first estimate a regression model that we can use to predict income. 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.[19] 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. We run this prediction model separately by gender so that we estimate predicted income from a gender-specific earnings model.

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 use the predicted female share rather than the actual share in part 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

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

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.[20]

To get an initial sense of how the earnings effects of moving vary with $\hat{s}$, we run our event study specification separately for three groups of households. The first group is the sub-sample of households for which women are predicted to earn more than 50 percent of household income. In this sub-sample, the average $\hat{s}$ in this group is 52 in Germany and 54.2% in Sweden. We then construct a second group as the sub-sample of remaining households where the average $\hat{s}$ is equal to 1 minus the average $\hat{s}$ in the first group. In other words, we create a sub-sample of the remaining households in which men are predicted to earn, on average, the same share of household income as the women in the first group. This ends up being households in which women are predicted earn between 42.6% and 50% of household income in Germany and between 43.1% and 50% of household income in Sweden. Comparing these two groups of households allows us to test the qualitative prediction that households act "symmetrically" when the woman earns s% of household income versus when the man earns s%. The remaining households are placed in the third group in our analysis, which is households in which the woman are predicted to earn less than 42.6% in Germany and less than 43.1% of household income in Sweden (these households have average $\hat{s}$ of 35.4% and 38.3% in Germany and Sweden, respectively).

The results, shown in Figure 6, point to an asymmetry based on whether the man or the woman is predicted to earn more. The gender gap in earnings is largest among the couples in which the woman's predicted household income share is smallest (panels A and B). Focusing on couples in which the man or the woman has a predicted earnings share of roughly 45-46%, we see that men benefit more on average from relocation than women for households with $\hat{s} < 0.5$ (panels C and D), but women do not benefit more from relocation than men for households with $\hat{s} > 0.5$ (panels E and F). Since these samples are constructed to have a equal and opposite predicted shares of household income, then if the earnings gap were simply due to households maximizing joint income, we would expect to see the "equal and opposite" gender earnings gap among households in which women are predicted to earn more. Instead, we continue

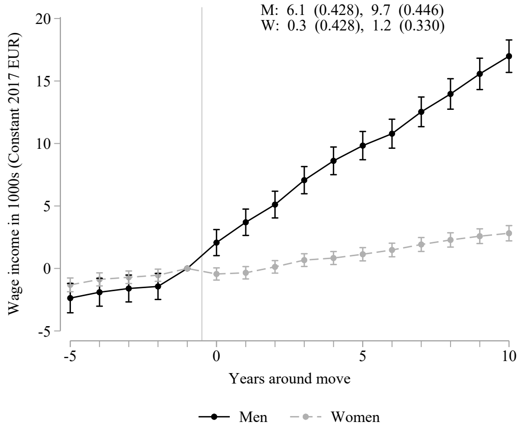
[20] Additionally, if households behave "as if" they value the income earned by the woman less than the income earned by the man, then women may choose to work less and earn less precisely because of this "discounting" of the woman's income within the household. That is, even when men and women have the same potential income, there will be a gender earnings gap within the household when $\beta < 1$ in models that allow for labor supply decisions in the household to respond to β. We assess this in our sensitivity analysis by re-estimating the predicted share of household income using a gender-blind earnings model.

to see a gender earnings gap favorite men in Germany and no gender gap favoring men or women in Sweden in the subset of couples where the women are predicted to earn more. Taken together, these results are our first pieces of evidence that $\beta < 1$ in both countries, with likely a bigger deviation in Germany because men *still* benefit more from relocation than women, even in households with $\hat{s} > 0.5$.

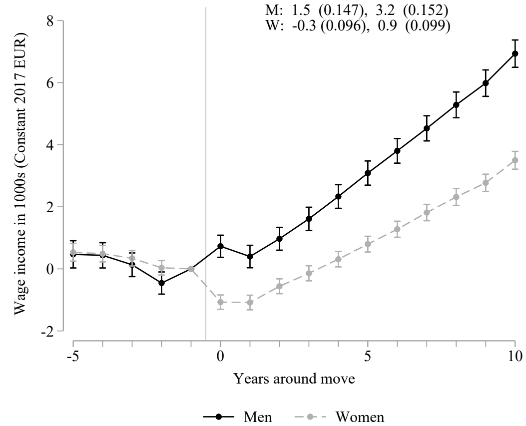
Our main results are based on estimates $\hat{s}$ that come from gender-specific income prediction models. Alternatively, we could use estimates $\hat{s}$ that come from a gender-blind income prediction model that assumes that women and men with identical education and experience have the same potential income and the same potential returns to migration. Appendix Figure OA-4 shows that we find broadly similar results using a gender-blind measure of predicted income. The results are slightly stronger in that in both countries in that we find that men still benefit more from relocation compared to women even when $\hat{s} > 0.5$ using a gender-specific measure of predicted income. We prefer to use the gender-specific income predictions in our baseline analysis because we do not other factors such as labor market discrimination to inform our estimate of β. Intuitively, if women earn less than men at a given level of education and experience, this could either reflect a gender norm that prioritizes the man's career, or labor market discrimination. By choosing a gender-specific income prediction we assume that any difference in income by gender conditional on education and experience comes from labor market factors rather than household decision. This is arguably somewhat conservative because if households discount income earned by the woman then women may choose to work less and earn less income than than men even if they have same potential income.

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

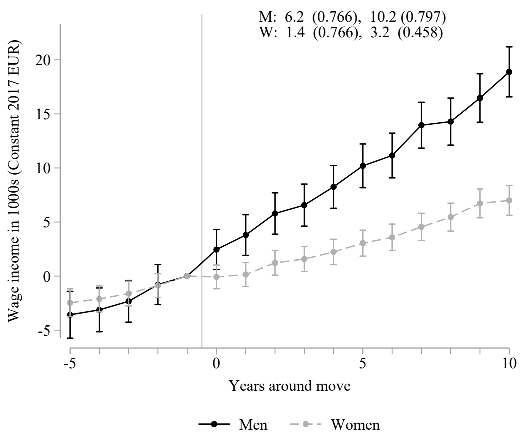
(a) Female Share of HH Income $< 43\%$, Germany



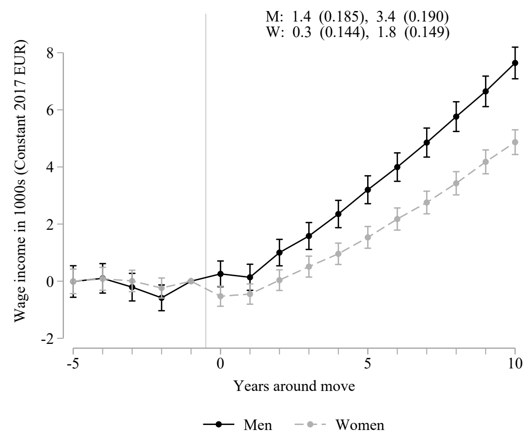
(b) Female Share of HH Income $< 43\%$, Sweden



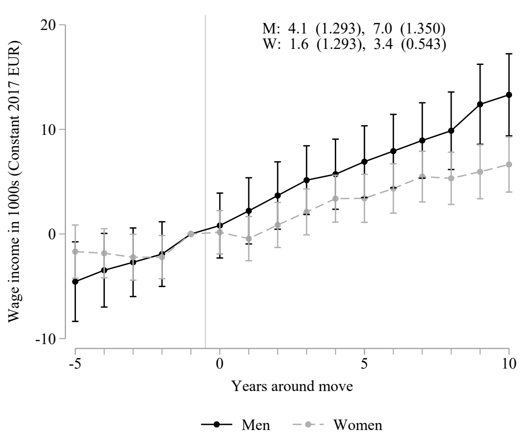
(c) Female Share of HH Income $\in [43, 50)\%$, Germany



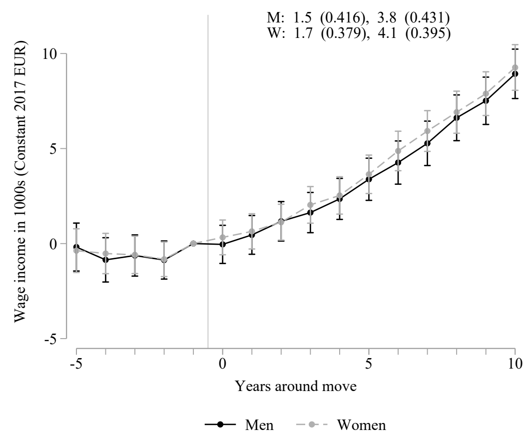
(d) Female Share of HH Income $\in [43, 50)\%$, Sweden



(e) Female Share of HH Income $\geq 50\%$, Germany



(f) Female Share of HH Income $\geq 50\%$, 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.

We summarize the results from this heterogeneity analysis in Table 4 which reports the effects of relocation on earnings for men and women in the full sample and in each of the three sub-samples defined by $\hat{s}$. The first three rows of this table give the six moments for each country that are used in the model-based analysis.

Comparing across the columns, we see that in both countries in the two $\hat{s} < 0.5$ sub-samples there are clear differences by gender. For these households, men's earnings increase by 10-15 percent in both countries, while women's income increase by much less in both Sweden and Germany.

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

	Germany		Sweden	
Predicted Female Share of Household Income, $\hat{s}$	Men (1)	Women (2)	Men (3)	Women (4)
$\hat{s} < 0.43$	9.7	1.2	3.2	0.9
	(0.4)	(0.3)	(0.2)	(0.1)
$\hat{s} \in [0.43, 0.50)$	10.2	3.2	3.4	1.8
	(0.8)	(0.5)	(0.2)	(0.1)
$\hat{s} \geq 0.50$	7.0	3.4	3.8	4.1
	(1.4)	(0.5)	(0.4)	(0.4)
Full sample	8.3	2.0	3.3	1.2
	(0.4)	(0.2)	(0.1)	(0.1)

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 gender-specific predicted female share of household income. The final row reports the estimates from the full sample for comparison.

Turning to $\hat{s} \geq 0.5$, we see in both countries the average return to migration is lower for men and higher for women (compared to $\hat{s} < 0.5$), but a gender gap remains at $\hat{s} \geq 0.5$ in Germany, though it is eliminated in Sweden. Taken together, these results are evidence against a standard collective model explaining our results, because the collective model would predict that women should be benefiting more than men in the $\hat{s} \geq 0.5$ sub-sample by the same degree that men benefit more the woman in the second sub-sample. The gap does "converge more" between men and women in Sweden compared to Germany, however, which is consistent with households deviating less from the collective household model in Sweden compared to Germany (i.e., β is closer to 1).

5.3 Model-Based Estimation

We now use the reduced-form estimates in Table 4 as moments to estimate the model parameters. We first calibrate the baseline distribution of income prior to migration in both countries. We do this by fitting a log normal income distribution for men and women in both countries based on the summary statistics in the year before the move. 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	3.49	3.18
Standard deviation of log income, men	0.77	0.61
Mean log income, women	2.58	2.54
Standard deviation of log income, women	0.90	0.73
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	0.04	-0.06
Standard deviation in the returns to migration, σ_r	0.03	0.21
Household mobility cost, c	7.75	3.63
Relative weight on woman's income compared to man's income, β	0.63	0.79

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 for $\hat{s} < 0.5$ and $\hat{s} \geq 0.5$ reported in Table 4.

With the baseline income parameters calibrated, there are four remaining model parameters: the mean and standard deviation parameters governing the returns to migration for men and women (μ_r and σ_r), the household mobility cost (c), and the non-collective household parameter (β).[21]

[21] In our baseline model we assume that all households have the same mobility cost. We can easily extend model to allow for heterogeneity in household mobility costs. Specifically, we can assume that household mobility costs are independently and normally distributed with parameters μ_c and σ_c. Using external information on the migration rate (i.e., the share of households that move during sample period), then we can use the migration rate as an additional moment to estimate σ_c separately from the other parameters. Importantly, this does not affect the identification and estimation of the other parameters;different values of the migration rate will not affect estimated values of the other parameters but will only affect estimates of σ_c. As a result, we ignore heterogeneity in mobility cost for simplicity, since β is our primary parameter of interest.

To identify and estimate these four model parameters, we use the six moments in Table 4 which represent the average change in income from relocation for men and women in the three sub-samples that group households based on $\hat{s}$. Intuitively, the identification works as follows: if $\beta = 1$, then the average change in income for men and women at $\hat{s} = 0.5$ should be the same according to Proposition 2. This tells us that the extent to which women do not benefit more than men in the $\hat{s} \geq 0.5$ sub-sample primarily identifies the parameter β. The identification of the other three parameters is more subtle, but they are jointly identified by the relative income gaps between men and women in the two groups where $\hat{s} < 0.5$ compared to the $\hat{s} \geq 0.5$ group, given β.

To estimate the model parameters, we simulate the model a large number of times and search for the combination of model parameters which minimize the sum of the squared distance between the moments and the simulated values of the moments from the model, weighting each moment by the inverse of the sampling variance of each estimated moment reported in Table 4.[22] We account for the fact that $\hat{s}$ is a noisy estimate by simulating a measure of predicted income that has the same R^2 as the actual R^2 in each gender-specific prediction model. This ensures that the simulated $\hat{s}$ has the same amount of noise as the empirical $\hat{s}$ used to define the sub-samples used in the reduced-form empirical analysis.[23]

The model-based parameters are reported in Panel B of Table 5. The estimated distribution of the returns to migration is is similar in both countries, with slightly greater dispersion in returns in Germany as compared to Sweden. We find larger mobility costs in Germany, although the baseline income is larger so as percentage of baseline income the mobility costs are more similar. The estimated household mobility cost is large in both countries, consistent with previous evidence that household migration is drive by income prospects but that households face large migration costs (see, e.g., Kennan and Walker 2011).

Our primary parameter of interest is the β parameter, which is estimated to be $\beta = 0.81$ (standard error XX) in Sweden and $\beta = 0.60$ (standard error XX) in Germany. In both countries, we see that the 95 percent confidence interval around the β estimate excludes 1, so we reject the collective household model in both countries.

[22] In the Appendix, we report similar estimates from an alternative two-step approach. In this approach, we first estimate the standard deviation of the returns to migration parameter and the mobility cost parameter using two moments which are the average earnings effects of relocation for men and women in the full sample, implicitly assuming that the mean returns to migration are 0. Then, in the second step, we estimate the β parameter and the mean returns to migration parameter using the same six moments used in the main analysis. Appendix Table OA-3 shows that we get very similar results from this alternative procedure, indicating that the mobility cost and returns to migration parameters are robust to alternative approaches, and our estimate of β is primarily identified by the relative gender gaps across subgroups, holding constant the other model parameters.

[23] Intuitively, a noisy measure of $\hat{s}$ biases us towards seeing similar gender gaps across sub-samples, which will tend to bias downward the estimate of β and lead to rejecting the collective household model because of measurement error.

One way to assess the economic importance of $\beta < 1$ is to re-simulate the model with $\beta = 1$. Panel A of Table 6 shows the empirical estimates, and Panel B shows the simulated moments at the chosen model parameters, indicating an extremely good model fit. Panel C of Table 6 shows imposing $\beta = 1$ (and holding other parameters constant) results in a somewhat worse model fit, particularly for the $\hat{s} \geq 0.5$ sub-sample. An alternative approach is to re-estimate the model restricting $\beta = 1$; Panel D of Table 6 shows that this model also has a worse fit, particularly for Germany.[24]

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 collective 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 collective model in Germany is interesting because Germany also has a larger baseline gender gap (and, as we discuss below, 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.

[24]The estimated model parameters in the restricted model that re-estimates the other model parameters imposing $\beta = 1$ in each country are reported in Table OA-2.

Table 6: Assessing Model Fit

Predicted Female Share of Household Income, $\hat{s}$	Germany Men (1)	Germany Women (2)	Sweden Men (3)	Sweden Women (4)
Panel A: Empirical Estimates				
$\hat{s} < 0.43$	9.7	1.2	3.2	0.9
$\hat{s} \in [0.43, 0.50)$	10.2	3.2	3.4	1.8
$\hat{s} \geq 0.50$	7.0	3.4	3.8	4.1
Panel B: Simulated Moments from Baseline Model				
$\hat{s} < 0.43$	9.64	1.08	3.23	0.80
$\hat{s} \in [0.43, 0.50)$	10.25	3.34	3.24	1.80
$\hat{s} \geq 0.50$	7.01	3.39	3.88	4.14
χ^2 goodness-of-fit statistic	0.019		0.021	
Panel C: Simulated Moments Setting $\beta = 1$ (holding other parameters constant)				
$\hat{s} < 0.43$	8.08	2.24	2.73	1.07
$\hat{s} \in [0.43, 0.50)$	6.59	4.95	2.69	2.02
$\hat{s} \geq 0.50$	4.52	4.21	3.24	4.16
χ^2 goodness-of-fit statistic	4.478		0.360	
Panel D: Simulated Moments Restricting to $\beta = 1$ (re-estimating other parameters)				
$\hat{s} < 0.43$	10.22	1.03	3.13	1.01
$\hat{s} \in [0.43, 0.50)$	8.40	4.94	2.96	2.08
$\hat{s} \geq 0.50$	5.13	4.78	3.45	4.53
χ^2 goodness-of-fit statistic	2.375		0.193	

Notes: This table presents the empirical estimates of the effects of moving for $\hat{s} < 0.5$ and $\hat{s} \geq 0.5$ 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.

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	1.80	1.29	1.55	1.33
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	-0.05	-0.55	-0.05	-0.17
Implied share of Female "child penalty" accounted for the country-specific β estimate		90.2%		65.0%

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).

5.4 Additional Implications of $\beta < 1$: Gender Differences in the 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 an exogenous job separation, 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 estimates of the effects of job separations caused by mass layoff events. We view this a useful "out-of-sample" test of model fit because the estimated effects of the mass layoff events on the probability of relocating by gender were not directly targeted in the model-based estimation. For this exercise, we simulate the model at the parameters estimated in each country (reported in Table 5), and we exogenously reduce income by the man or woman by the average long-term earnings losses from job displacement estimated in prior work, and we simulate the resulting change in the probability of moving following job displacement.[25] The results in Panel A of Appendix Table 7 show that the model can accurately reproduce a gender gap in the effects of a job layoff on the probability of

[25] We calibrate the average earnings losses of job displacement for men and women to be 25.4 percent for men and 34.6 percent for women in Germany based on the recent estimates from XX. For Sweden, we calibrate the average earnings losses to be 16.4 percent for men and women based on the estimates in XX and the evidence in XX that finds very small gender differences in earnings losses by gender in Sweden.

moving. The model reproduces the reduced-form results fairly well, though it somewhat under-predicts the gender gap in Germany and somewhat over-predicts the gender gap in Sweden. One reason the model does not perfectly reproduce the reduced-form results is that in our model simulations we assume that the potential income draws (used in determining whether the household relocates) is not affected by job displacement; this is unlikely to be fully accurate if specific human capital is destroyed, since this will also reduce potential income in other local labor markets. Moreover, to the extent this varies across countries or by gender, this will lead our model to diverge from the actual reduced-form estimates. Given these limitations, the fact that our model does a fairly good job reproducing the reduced-form results shows that these other factors are likely less important that account for the non-collective nature of household decision-making in this context.

As an additional application of our model, 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. We therefore explore the possibility that the child penalty is partly due to households putting less weight on income declines by the woman (as compared to the man), even if the man and woman in a household have equal ability in child-rearing and equal preferences for reducing labor supply following the birth of their first child. We provide full details in Appendix A.5 and we report results in Panel B of Appendix Table 7. Perhaps surprisingly, we find that we can quantitatively account for a majority of previously-estimated child penalty in both countries. We do not fully account for the child penalty, however, which could be due to other factors that we assume away in the exercise (e.g., men and women may not actually have equal comparative advantage in child rearing relative to market work). However, we view this stylized exercise as raising the intriguing possibility that the existing child penalty literature is partly capturing a gender norm that prioritizes the man's career.[26]

[26]Consistent with this tentative interpretation, our finding that the gender gap in the earnings effects of relocation is smaller in couples in which at least one spouse is of East Germany origin lines up with the small estimated child penalty in these same couples, compared to couples in which neither spouse is of East German origin.617-944-9962

6 Additional Evidence of Norms: East and West Germany

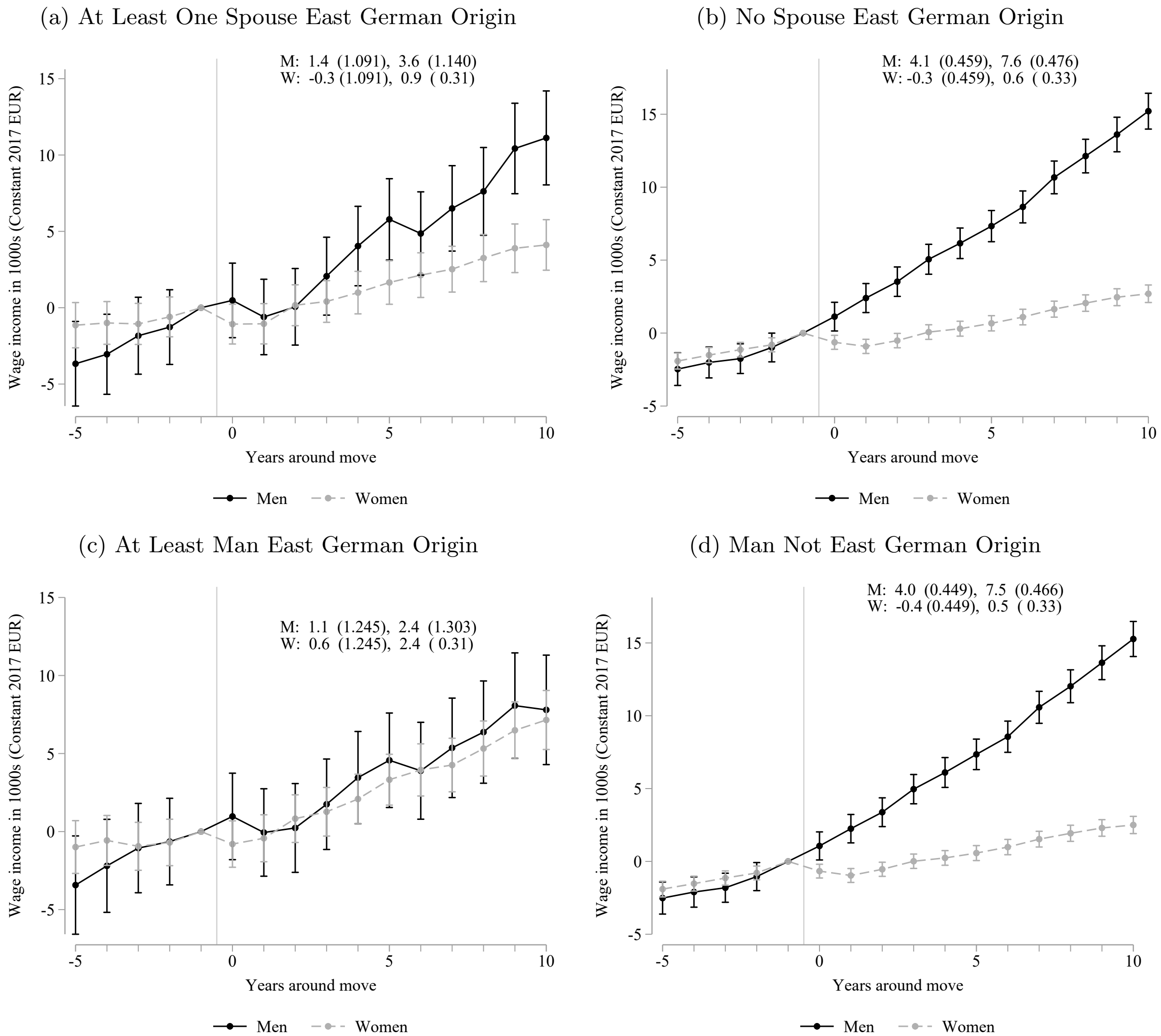
As a more direct test of whether culture or norms explain part of the earnings gap, we test whether the gap varies based on whether men and women are of East or West German origin. East Germany has relatively high rates of female labor force participation due to its history as a socialist state where women were strongly encouraged to work. Existing research has shown that whether women grow up in East or West Germany influences decisions concerning labor supply (Boelmann et al. 2021). We use couples' family origins as a source of variation in gender norms. We approximate origins with the first labor market entry similar to Boelmann et al. (2021).

We first run our event study but split into couples in which neither spouse is from East Germany and those in which at least one spouse is from East Germany. We focus on couples currently living in West Germany. The results are shown in panels (a) and (b) of Figure 7. The gender gap in earnings among couples in which neither spouse is from East Germany is large, with a long-run earnings gap of 7.1 percentage points. The gap is substantially smaller, at 2.7 percentage points among couples that have at least one spouse from East Germany. This is in line with a gender norms story: Women are substantially more likely to work in East than in West Germany, and so it is likely that an individual born in East Germany saw his or her mother working.

In panels (c) and (d), we focus exclusively on couples in which the man is of East German origin. Fernandez et al. (2004) present evidence that men who are exposed to a working mother have more liberal gender attitudes. Our results support this hypothesis and provide additional evidence of a gender norm. If the man is not of East German origin (panel d), the gender gap in earnings is large, but if the man is of East German origin, the gap disappears.

Since the couples in which a spouse is from East Germany have somewhat lower income, we re-weight the East Germany and West German couples to have the same distribution of age and income (overall and by gender). The results in Appendix Figure OA.XX shows similar patterns after re-weighting the couples in this way, indicating that the small differences between the groups does not account for the patterns in Figure 7.

Figure 7: East vs. West German Origin



7 Alternative Explanations

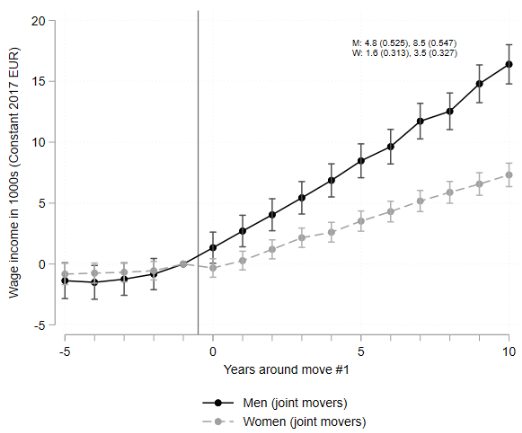
We have provided evidence that the results do not fit a collective household model and instead suggest that a gender norm explains the difference in men's and women's earnings following a move. In this section we explore three alternative explanations for our findings. First, we test whether couples anticipate that women will leave the labor market upon having a child and so even if women have a high predicted share of earnings, couples know that it the woman's earnings will actually be lower. Second, we test whether the results are driven by women selecting into occupations that have lower returns to moving. Finally, we explore the possibility that women's lower returns to moving are made up for by a non-wage amenity.

Anticipating the "Mommy Track" In our modelling exercise, we predicted men's and women's earnings four years after a move based on their observable characteristics. It is plausible that women anticipate leaving the labor market or reducing their work hours following the birth of a child, and therefore know that their earnings will be lower than that of their husbands. In this case, it may make sense for couples to prioritize the man's career, even if each spouse's predicted earnings are similar in the absence of a child (or if childcare was split evenly).

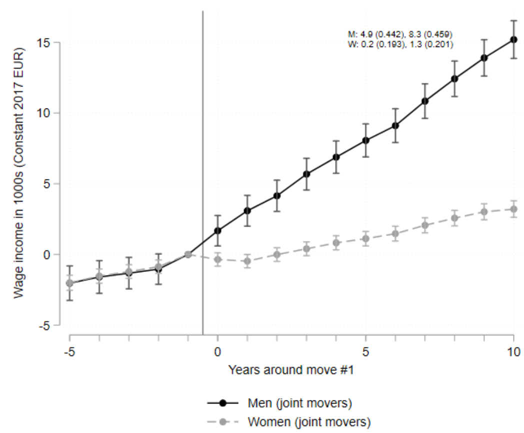
We test this possibility by restricting to couples that do not have children in our sample period. Figure 8 compares the event study results for couples that do not have children in the sample period (panel A) and couples that have children (panel B) for Germany. The long-run earnings gap between men and women is only slightly larger for couples with children (0.26 percentage points) than for couples without (0.22 percentage points). It is therefore unlikely that the anticipation of the "motherhood penalty" is driving the result.[27].

Figure 8: Wage Income Results by Children, Germany

(a) No Children in Our Sample Period



(b) Children



Occupation Selection Given that women tend to be in occupations with lower wage growth, it is possible that these same jobs have lower returns to moving. To test whether this can account for some of our main results, we estimate our event study equation but re-weight the sample so that women have the same occupation distribution as men.[28] We can only carry out this analysis in Germany because we have detailed occupation codes in the Germany administrative data but not in the Swedish administrative

[27] In addition, the motherhood penalty may in itself be the result of a gender norm, as argued in Kleven (2023) and in Appendix Section XX

[28] To do this, we limit our movers sample to couples in which both individuals are working in occupations with at least 10 individuals in the occupation, within our sample of movers. We further restrict to occupations that have at least one man and one woman. We then re-weight the sample so that the women in the sample have the same occupation distribution as men. Occupations are defined at the 4-digit level for this analysis.

data. Appendix Figure XX shows the results for the German couples for the three groups defined based on the women's predicted share of household income. We also include the unweighted regression results for comparison (Panels XX and XX respectively), and the results are very similar between the unweighted and re-weighted panels, across each sample. Since the results are therefore largely unchanged, we conclude that occupational sorting and differences in returns to moving by occupation are not driving our main results.

Non-wage Amenities It is possible that women's returns to moving come in the form of non-wage amenities. For example, research has shown that women choose jobs with shorter commute times (Le Barbanchon et al. 2020). A couple could therefore be treating each member equally but women benefit from a shorter commute whereas men benefit from a higher salary or wage. To explore this possibility, we look at how distance to work changes following a move. Figure OA-14 shows that, while men's average commute increases slightly, women's average distance from work does not change. We also test whether couples move to "better" commuting zones by plotting the mean commuting zone fixed effect of the CZ a couple moves from and to.[29] We small a small increase in the average CZ quality that couples move to in Germany and a small decline in Sweden (Appendix Figure OA-13). However, these changes are so small that they are unlikely to explain the results. It is possible that women are moving to firms that are offering other non-wage amenities, but we are unable to test for this in our data.

Finally, couples could be moving to be closer to grandparents, to help with child-rearing for example. This explanation would be in line with the Anstreicher and Venator (2022), who find that American women tend to move back to their home locations in anticipation of childbirth. To explain the gender earnings gap that emerges in our case, it would need to be that couples only move to grandparents when the man can be compensated for doing so in the form of a higher wage, and that women do not work more or earn more in these areas. We can test whether couples move to live near grandparents using the Swedish data, where we can link family members over generations (we are unable to link the parents to their children's grandparents in the Germany data). Appendix Figure OA-14 shows no evidence that couples move closer to any grandparent or move close to a maternal grandparent.

[29]The fixed effects are from a regression estimating the contribution of commuting zones to earnings.

8 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 collective 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 collective 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 collective 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. We want to show the following integral is positive, where $f(s)$ is the pdf of s:

$$\int_0^1 E[\Delta y_M - \Delta y_F | \Delta y_M + \Delta y_F > c] \cdot f(s) ds$$

Rewriting with the simplified form of the expression, we have:

$$\int_0^1 (1-2s) \left[\mu_r y_1 + \lambda \left(\frac{c - \mu_r y_1}{\sigma_r y_1 \sqrt{(1-s)^2 + s^2}} \right) \left[\frac{\sigma_r y_1}{\sqrt{(1-s)^2 + s^2}} \right] \right] \cdot f(s) ds =$$

$$= \underbrace{\int_0^1 (1-2s) \mu_r y_1 \cdot f(s) ds}_{A} + \underbrace{\int_0^1 (1-2s) \lambda \left(\frac{c - \mu_r y_1}{\sigma_r y_1 \sqrt{(1-s)^2 + s^2}} \right) \left[\frac{\sigma_r y_1}{\sqrt{(1-s)^2 + s^2}} \right] \cdot f(s) ds}_{B}$$

We start with the first part of the expression, integral A. Assuming $s \in [0,1]$, then $\int_0^1 f(s) ds = 1$.

$$\begin{aligned} \int_0^1 (1-2s) \mu_r y_1 \cdot f(s) ds &= \mu_r y_1 \int_0^1 (1-2s) f(s) ds \\ &= \mu_r y_1 \left[\int_0^{0.5} (1-2s) f(s) ds + \int_{0.5}^1 (1-2s) f(s) ds \right] \end{aligned}$$

We take the second integral from the expression above and integrate by substitution. Let $x = 1 - s$ and $dx = -ds$.

$$\begin{aligned} \int_{0.5}^1 (1-2s) f(s) ds &= \int_{0.5}^0 (1 - 2(1-x)) f(x)(-1) dx \\ &= \int_{0.5}^0 (-1)(1-2x) f(1-x)(-1) dx \\ &= -\int_0^{0.5} (1-2x) f(1-x) dx \end{aligned}$$

Returning to integral A:

$$\int_0^1 (1-2s) \mu_r y_1 \cdot f(s) ds = \mu_r y_1 \left[\int_0^{0.5} (1-2s) f(s) ds + \int_{0.5}^1 (1-2s) f(s) ds \right]$$

$$= \mu_r y_1 \left[\int_0^{0.5} (1-2s) f(s) ds - \int_0^{0.5} (1-2x) f(1-x) dx \right]$$

We can combine the integrals in the last line because they have the same bounds of integration. Additionally, in the second integral, we defined the variable x, but the name of the variable itself is arbitrary so we can change it back to s for simplicity.[30]

$$\int_0^1 (1-2s)\mu_r y_1 \cdot f(s) ds = \mu_r y_1 \left[\int_0^{0.5} (1-2s)[f(s) - f(1-s)] ds \right]$$

Recall that if $f(x) \geq 0$ for $x \in [a,b]$, then $\int_a^b f(x)dx \geq 0$. In this case, we want to show that the function we are integrating is positive. Note that μ_r and y_1 are positive because they are the mean of the second period income and the first period household income, respectively. Additionally, $(1-2s)$ is positive between $(0, 0.5]$. Thus, for integral A to be positive, we have to show that $f(s) - f(1-s) > 0$.

The function, $f(s)$, is the PDF of s. To find the PDF of s, we have to determine its distribution. The first period incomes, y_{i1} for $i \in \{M, F\}$, have log-normal distributions, and s is a ratio of the incomes and has a logit-normal distribution, shown below.[31]

$$\begin{aligned}
s &= \frac{y_{F1}}{y_{F1} + y_{M1}} \\
&= \frac{1}{1 + y_{M1}/y_{F1}} \\
&= \frac{1}{1 + e^{ln(y_{M1}/y_{F1})}} \\
&= \frac{1}{1 + e^{-[ln(y_{F1}) - ln(y_{M1})]}} \\
\implies f(s) &= \frac{1}{\sigma\sqrt{2\pi}} e^{-(\text{logit}(s)-\mu)^2/(2\sigma^2)} \frac{1}{s(1-s)} \\
\mu &= \mu_F - \mu_M < 0 \\
\sigma &= 2\sigma^2
\end{aligned}$$

Plugging this back into integral A, we have:

$$f(s) - f(1-s) = \frac{1}{\sigma\sqrt{2\pi}} \frac{1}{s(1-s)} \left[e^{-(\text{logit}(s)-\mu)^2/(2\sigma^2)} - e^{-(\text{logit}(1-s)-\mu)^2/(2\sigma^2)} \right]$$

[30] Because we are considering s and x in separate integrals, we are able to do this. However, if s and x were within the same integral, and we were evaluating a double integral, then we would not be able to combined these integrals.

[31] The logit-normal PDf is defined only for $s \in (0,1)$. Thus, to evaluate $f(s)$, we actually need to solve the improper integral between $(0,1)$. Thus, for the rest of this proof, we will let $\int_0^1 f(s)ds = \int_{\to 0}^{\to 1} f(s)ds$. For our purposes, we will also assume that $f(0) = 0$ and $f(1) = 1$.

$$= \frac{1}{\sigma\sqrt{2\pi}} \frac{1}{s(1-s)} e^{-1/(2\sigma^2)} \left[e^{(\text{logit}(s)-\mu)^2} - e^{(\text{logit}(1-s)-\mu)^2} \right]$$

To simplify the exponents of e, we use the following facts:

$$\begin{aligned} \text{logit}(s) &= log\left(\frac{s}{1-s}\right) = log(s) - log(1-s) \\ \text{logit}(1-s) &= log\left(\frac{1-s}{1-1+s}\right) = log(1-s) - log(s) \\ &= -\text{logit}(s) \end{aligned}$$

Let $\eta = \text{logit}(s)$. Returning to simplifying the expression for $f(s) - f(1-s)$:

$$\begin{aligned} f(s) - f(1-s) &= \frac{1}{\sigma\sqrt{2\pi}} \frac{1}{s(1-s)} e^{-1/(2\sigma^2)} \left[e^{\eta^2 - 2\mu\eta + \mu^2} - e^{(-\eta)^2 + 2\mu\eta + \mu^2} \right] \\ &= \frac{1}{\sigma\sqrt{2\pi}} \frac{1}{s(1-s)} e^{-1/(2\sigma^2) + \eta^2 + \mu^2} \left[e^{-2\mu\eta} - e^{2\mu\eta} \right] \\ \implies f(s) - f(1-s) &> 0 \end{aligned}$$

To summarize, considering all the components of integral A, we see that integral A is positive:

$$\begin{aligned} \int_0^1 (1-2s)\mu_r y_1 \cdot f(s)ds &= \underbrace{\mu_r y_1}_{>0} \left[\int_0^{0.5} \underbrace{(1-2s)}_{>0} \underbrace{[f(s) - f(1-s)]}_{>0} ds \right] \\ &> 0 \end{aligned}$$

Now looking at integral B:

$$\int_0^1 (1-2s)\lambda \left(\frac{c - \mu_r y_1}{\sigma_r y_1 \sqrt{(1-s)^2 + s^2}} \right) \left[\frac{\sigma_r y_1}{\sqrt{(1-s)^2 + s^2}} \right] \cdot f(s)ds$$

Define $g(s) = \frac{k_1}{k_2\sqrt{(1-s)^2+s^2}}$ where k_1 and k_2 are constants. We want to show that the function C is symmetric over the line $x = 0.5$. This is equivalent to showing that $g(s) = g(1-s)$.

$$\begin{aligned} g(s) &= g(1-s) \\ \frac{k_1}{k_2\sqrt{(1-s)^2+s^2}} &= \frac{k_1}{k_2\sqrt{(1-(1-s))^2+(1-s)^2}} \\ \frac{k_1}{k_2\sqrt{(1-s)^2+s^2}} &= \frac{k_1}{k_2\sqrt{(-s)^2+(1-s)^2}} \end{aligned}$$

$$\frac{k_1}{k_2\sqrt{(1-s)^2+s^2}} = \frac{k_1}{k_2\sqrt{(1-s)^2+s^2}}$$

We can use this property of $g(s)$ to compare some of the terms in integral B. The terms, $\lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right)$ and $\frac{\sigma_r y_1}{\sqrt{(1-s)^2+s^2}}$, can both be written in terms of $g(s)$ with different k_1 and k_2. Given that $g(s)$ is symmetric about $x = 0.5$, we know that $\lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right)$ and $\frac{\sigma_r y_1}{\sqrt{(1-s)^2+s^2}}$ have the same values in the integrals when they are evaluated from $[0, 0.5]$ or $[0.5, 1]$.

Let $h(s) = \lambda\left(\frac{c-\mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2+s^2}}\right) \cdot \frac{\sigma_r y_1}{\sqrt{(1-s)^2+s^2}}$. Then integral B can be rewritten as:

$$\int_0^1 (1-2s)h(s)f(s)ds = \int_0^{0.5}(1-2s)h(s)f(s)ds + \int_{0.5}^1 (1-2s)h(s)f(s)ds$$

Following the same steps for simplifying integral A, we integrate by substitution for the second integral above. Let $x = 1-s$, $dx = -ds$.

$$\begin{aligned}\int_{0.5}^1 (1-2s)h(s)f(s)ds &= \int_{0.5}^0 (1-2(1-x))h(1-x)f(1-x)(-1)dx \\ &= -\int_0^{0.5}(1-2x)h(1-x)f(1-x)dx\end{aligned}$$

Combining the integrals:

$$\begin{aligned}\int_0^1 (1-2s)h(s)f(s)ds &= \int_0^{0.5}(1-2s)h(s)f(s)ds + \int_{0.5}^1 (1-2s)h(s)f(s)ds \\ &= \int_0^{0.5}(1-2s)h(s)f(s)ds - \int_0^{0.5}(1-2x)h(1-x)f(1-x)dx \\ &= \int_0^{0.5}(1-2s)[h(s)f(s) - h(1-s)f(1-s)]ds\end{aligned}$$

We have shown previously that $h(s)$ is symmetric about $s = 0.5$, so $h(s) = h(1-s)$. Therefore, whether integral B is positive depends on the sign of $f(s) - f(1-s)$. In simplifying integral A, we derived that $f(s) - f(1-s) > 0$, so this implies that integral B is also positive. Given that integral A and B are positive, this completes the proof that $\int_0^1 E[\Delta y_M - \Delta y_F | \Delta y_M + \Delta y_F > c] \cdot f(s)ds > 0$.

Lemma 1 *If $\mu_M > \mu_F$ and all households are collective 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, $E[\Delta y_M - \Delta y_F | s, \Delta y_M + \Delta y_F > c]$.

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

We want to show that when $0 < s < 0.5$, $E[\varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2}sy_1 \mid \varepsilon_{M2}(1-s)y_1 + \varepsilon_{F2}sy_1 > c] > 0$. Let $X = \varepsilon_{M2}(1-s)y_1$ and $Y = \varepsilon_{F2}sy_1$, with their distributions defined below. Recall that $\varepsilon_{i2} \sim N(\mu_r, \sigma_r^2)$. We assume $cov(X, Y) = 0$.

$$\begin{aligned}
X &= \varepsilon_{M2}(1-s)y_1 & Y &= \varepsilon_{F2}sy_1 \\
&\sim N((1-s)\mu_r y_1, ((1-s)y_1\sigma_r)^2) & &\sim N(s\mu_r y_1, (sy_1\sigma_r)^2)
\end{aligned} \tag{2}$$

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 collective 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-collective 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.

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

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

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

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, $0.5 y_1 \sigma_r (1 + \beta^3 - 2\beta^2)$, is in the open interval $(0, 0.5 y_1 \sigma_r)$. Because $0.5 y_1 \sigma_r > 0$, 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:

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

A.2 Additional Theoretical Results

In the section below, general derivations are provided based on the following normally distributed random variables.[32] 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: $E[X \mid X + Y > c - \mu_X - \mu_Y]$. In the first step below, we standardize the expectation (e.g. $\frac{x-\mu_x}{\sigma_x}$ where x is a random variable):

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

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

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 $s \sim N(0, 1)$.

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

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

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

- 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 $E[X \mid s] = \rho_{X,s}\left(\sigma_X/\sigma_S\right) \cdot s = \left(\sigma_{X,s}/\sigma_s^2\right) \cdot s$.

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 collective 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-collective 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:

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

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.

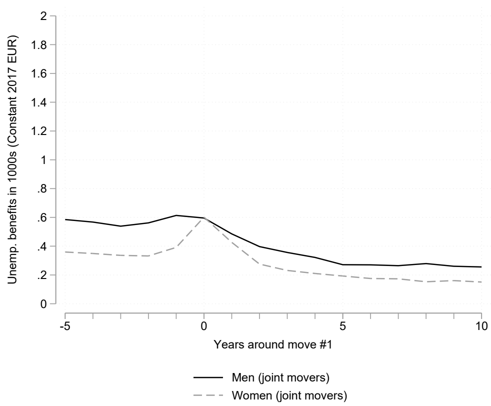
We choose $\eta_M = \eta_F = 1$, $\kappa = 0.1$, $\gamma = 0.5$, and we choose the baseline gender wage gap to be $w_F/w_M = 0.895$ in Sweden and $w_F/w_M = 0.82$ in Germany. We then simulate the model for $\lambda = 0$ and $\lambda = 0.25$ at the two different values of β and report the change in earnings 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

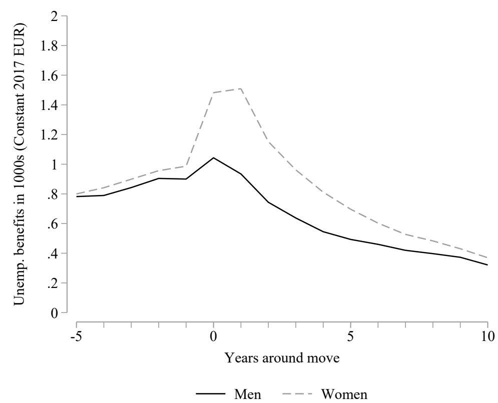
A.6 Other Employment Measures

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

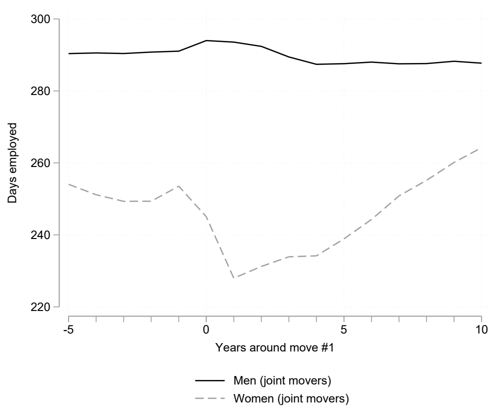
(a) Unemployment Benefits, Germany



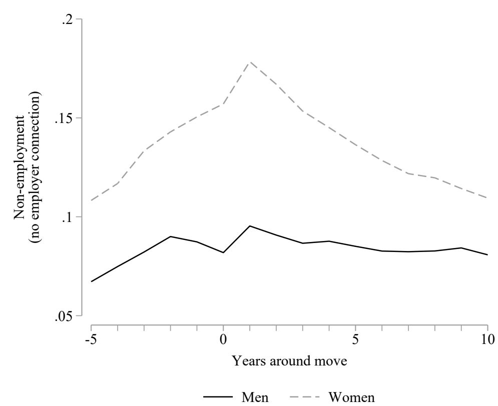
(b) Unemployment Benefits, Sweden



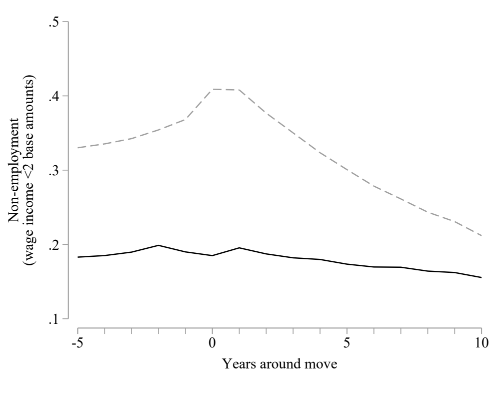
(c) Days Employed, Germany



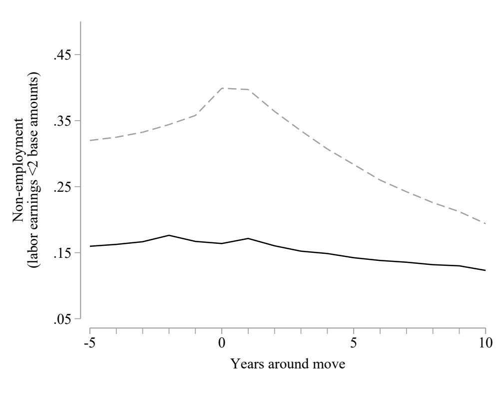
(d) No Employer Connection, Sweden



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



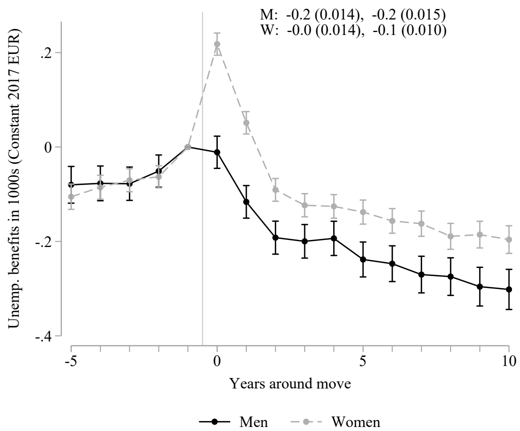
(f) Labor Earnings < 2 * Price Base Amounts, Sweden



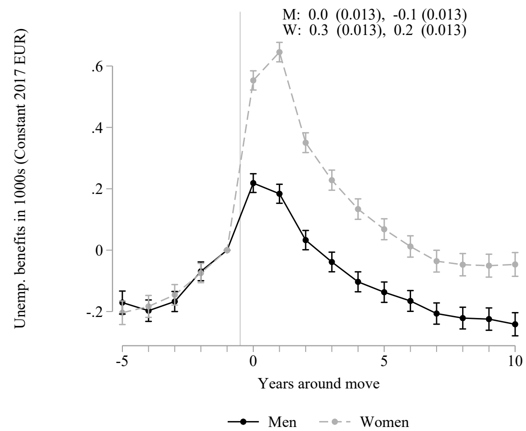
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first move, per gender.

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

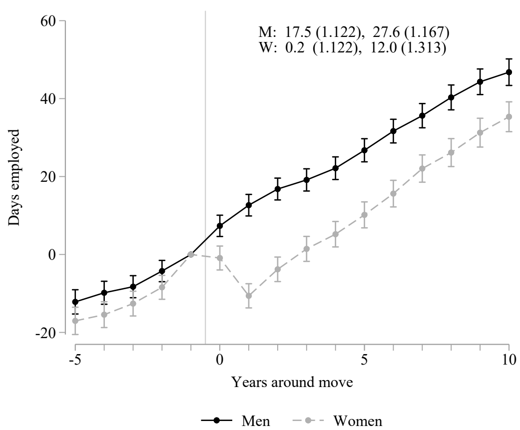
(a) Unemployment Benefits, Germany



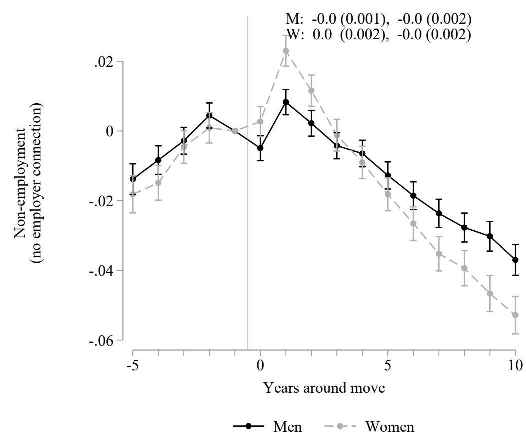
(b) Unemployment Benefits (Amount), Sweden



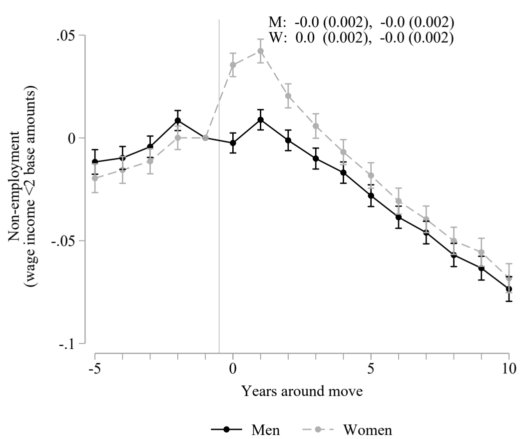
(c) Days Employed, Germany



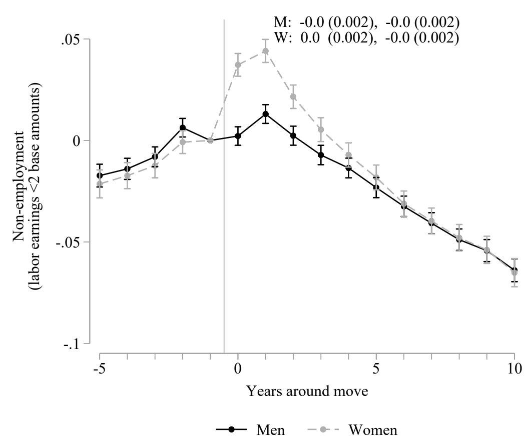
(d) No Employer Connection, Sweden



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



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



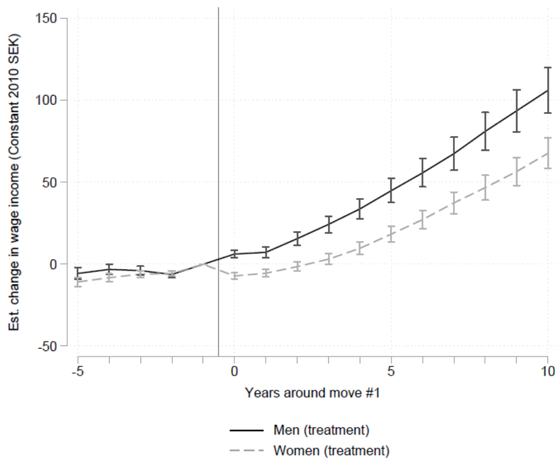
Notes: This figure displays the event study results that estimate the effect of moving on different outcomes in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The 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

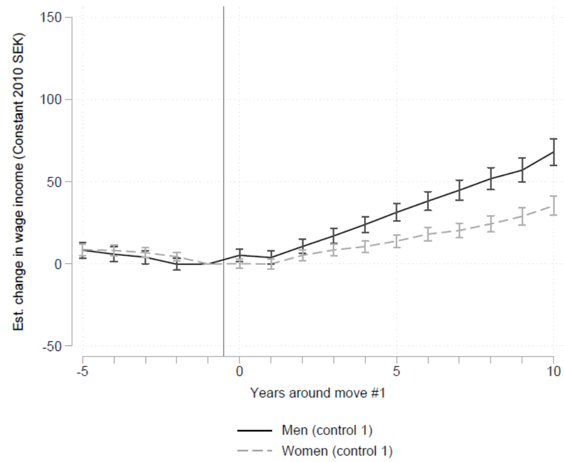
Figure OA-3: Impacts of Move on Wage Income - By Timing of First Joint Child, Sweden

Panel A

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

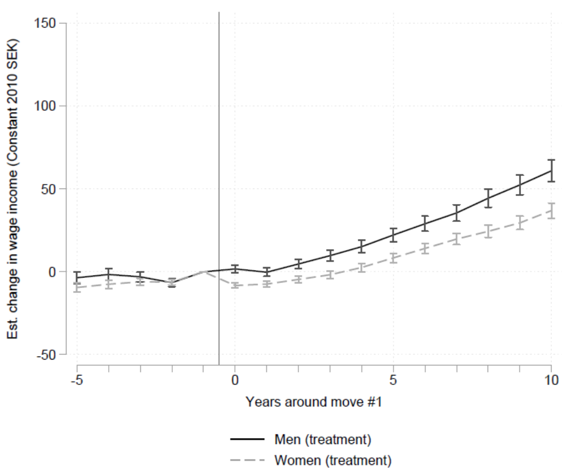


(b) No First Child Before $t+4$

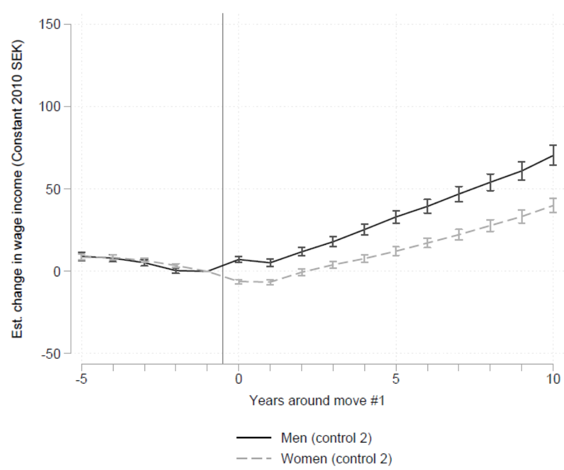


Panel B

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



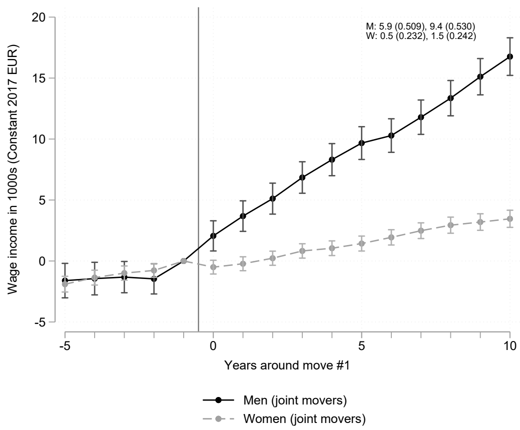
(d) No First Child in $(t-3, t+3)$



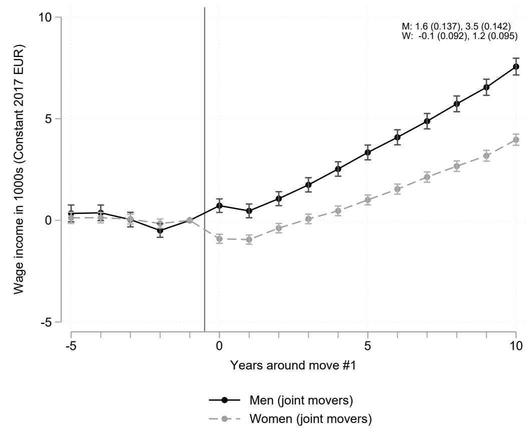
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move $(t-1)$ in Sweden. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. 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-blind Predicted Female Share of HH Income

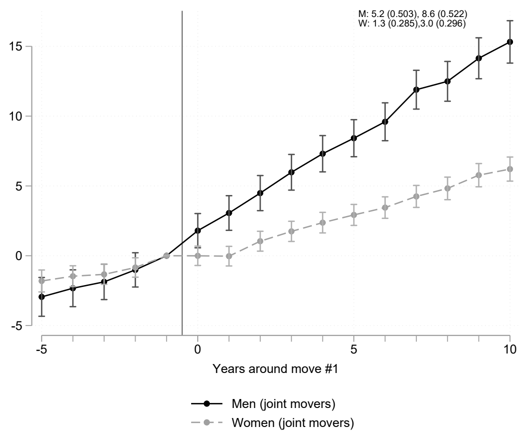
(a) Female Share of HH Income < 50%, Germany



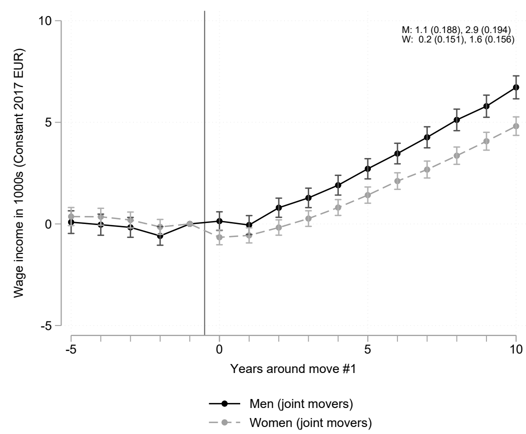
(b) Female Share of HH Income < 50%, Sweden



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



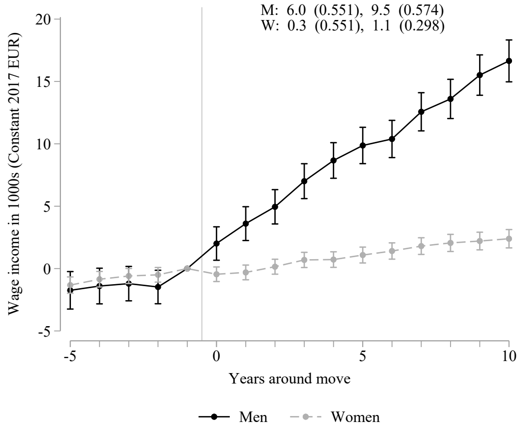
(d) Female Share of HH Income ≥ 50%, Sweden



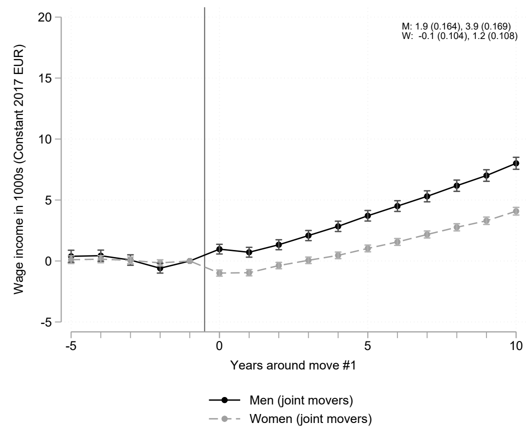
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions 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.

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

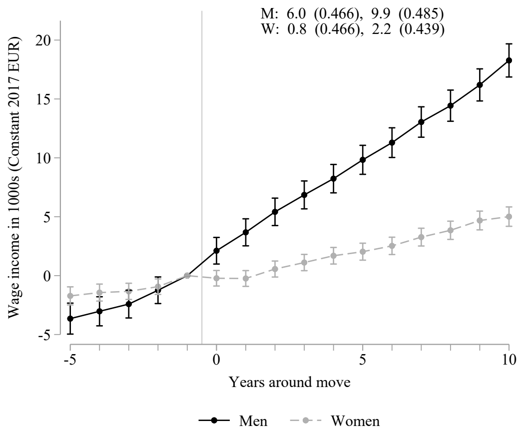
(a) Female Share of HH Income < Median, Germany



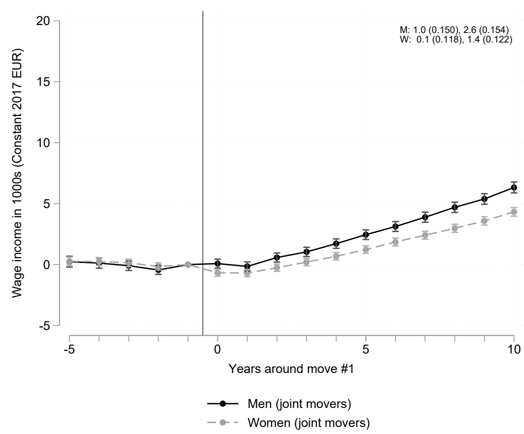
(b) Female Share of HH Income < Median, Sweden



(c) Female Share of HH Income $\geq$ Median, Germany



(d) 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
```

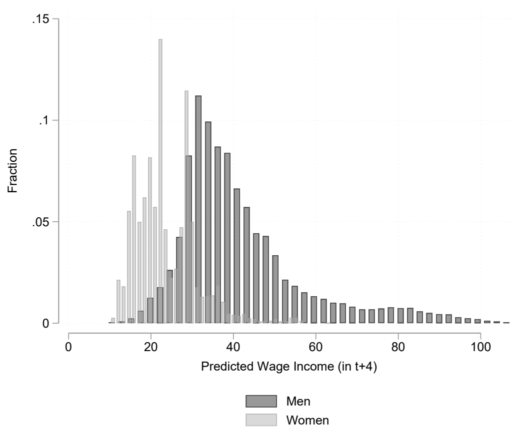
which controls for potential experience, number of children, college major (interacted with highest level of education), and year. In Germany, we do not have college major information so we replace with the highest level of education (three education categories: high school or less, vocational training,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

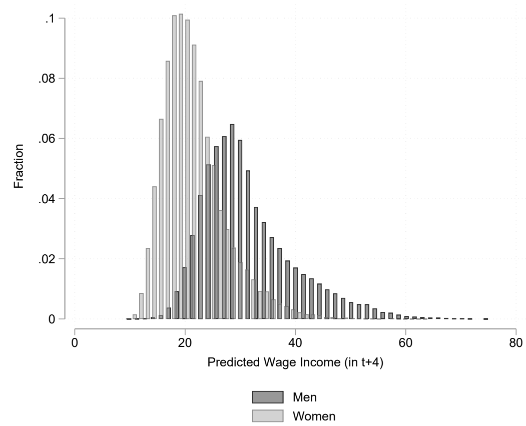
In the baseline analysis, we focus on *gender-blind* predictions so that the regression model above is run on men and women together. We also report results using *gender-specific* predictions where the regression model above is run on men and women separately.

Figure OA-6: Predicted Wage Income, Movers

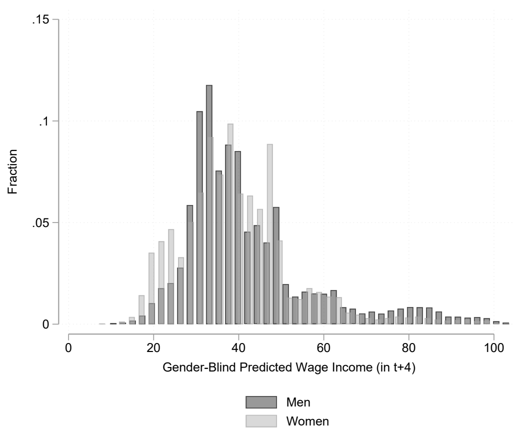
(a) Gender-specific, Germany



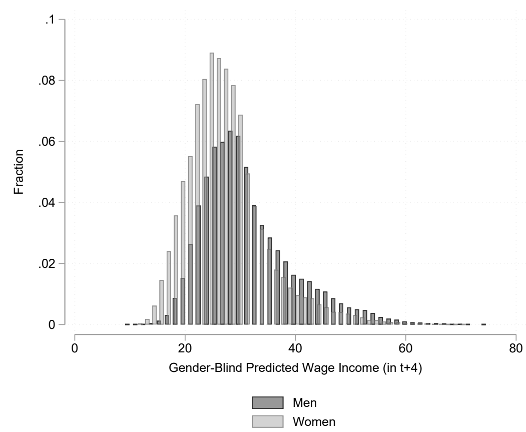
(b) Gender-specific, Sweden



(c) Gender-blind, Germany

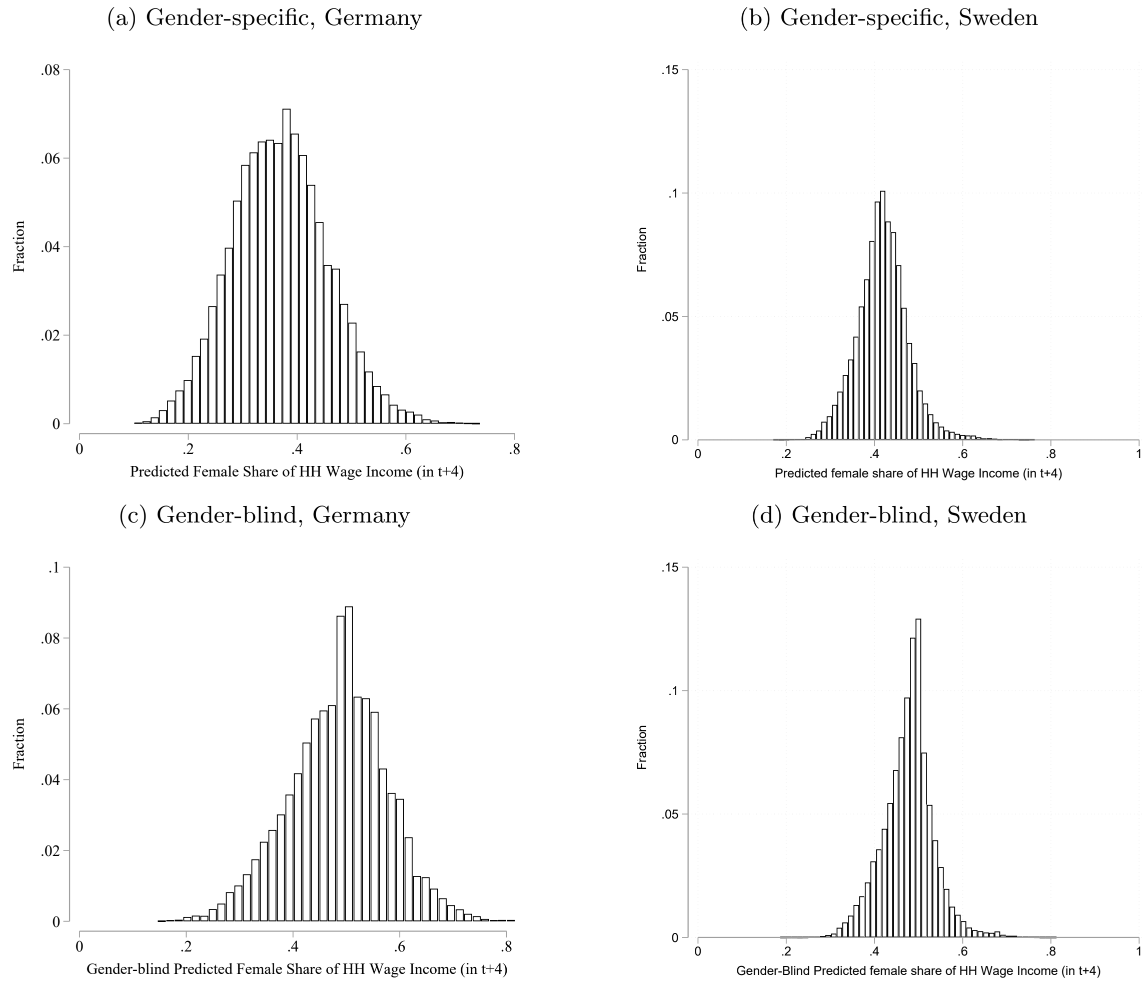


(d) Gender-blind, Sweden



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

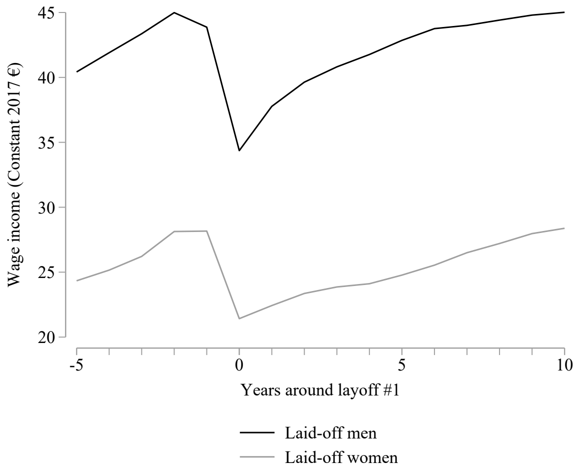


Notes: This figure displays histograms of predicted female share of household income by country on the movers sample. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 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.

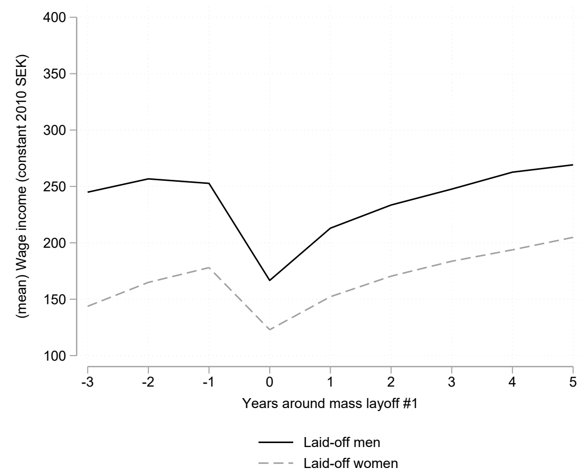
A.9 Descriptive figures for layoffs

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

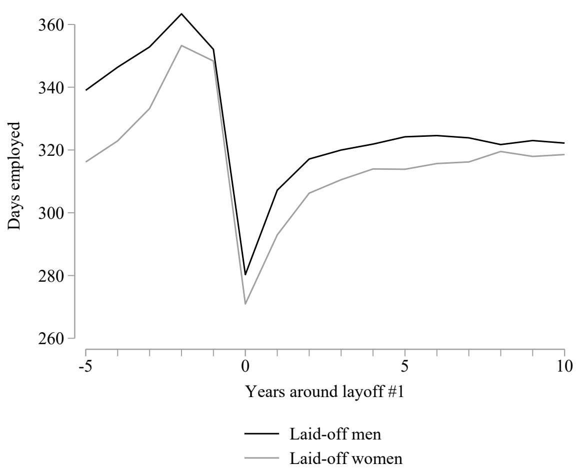
(a) Wage Income, Germany



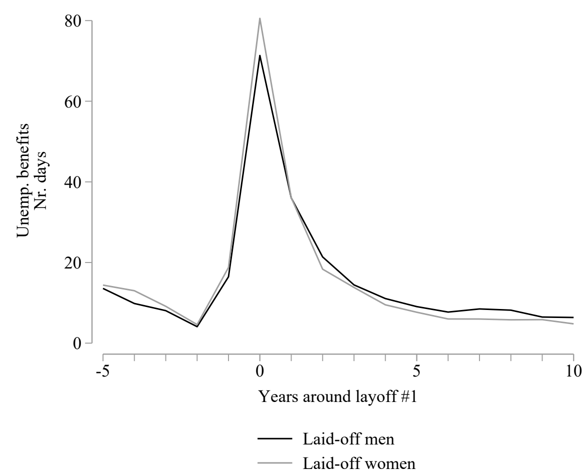
(b) Wage Income, Sweden



(c) Days Employed, Germany



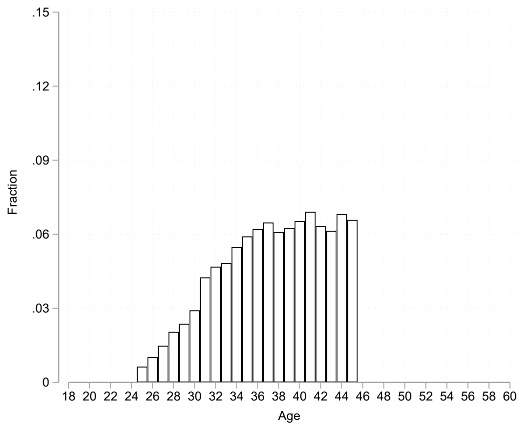
(d) Days UI Benefits , Germany



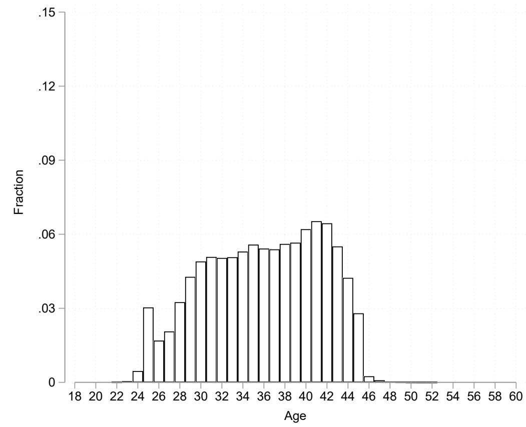
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first layoff event, per gender.

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

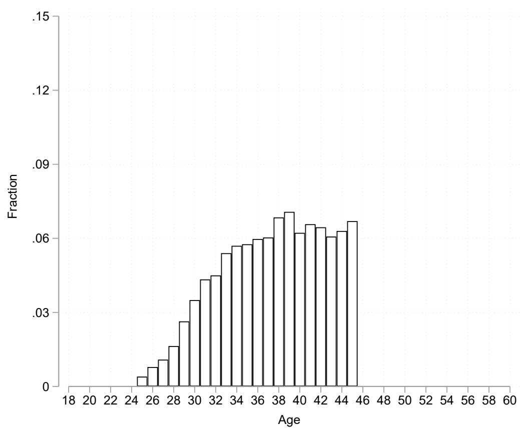
(a) True Layoffs, Women



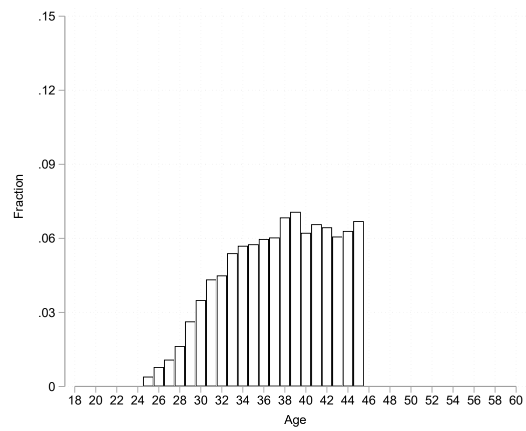
(b) Placebo Layoffs, Women



(c) True Layoffs, Men



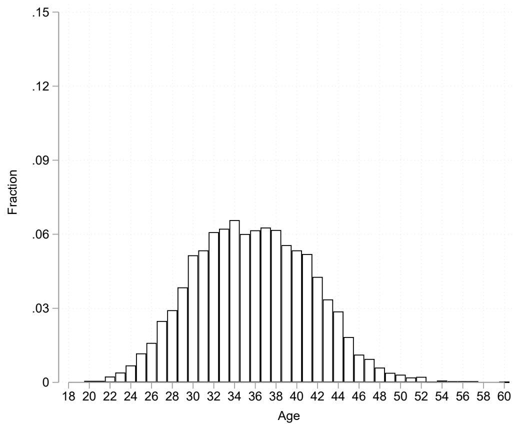
(d) Placebo Layoffs, Men



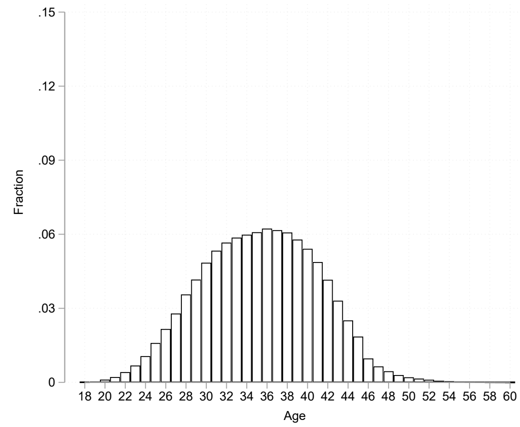
Notes: This figure displays histograms of age by gender for the laid-off individuals sample in Sweden.

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

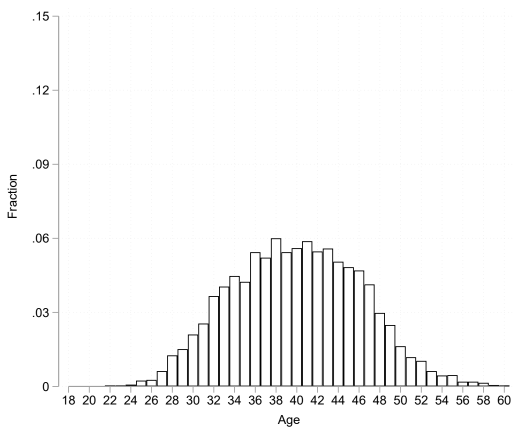
(a) True Layoffs, Female Partners



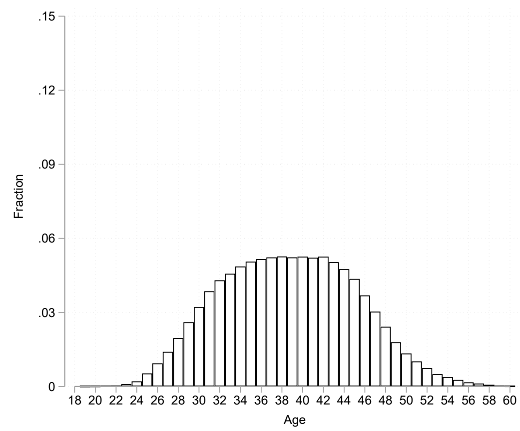
(b) Placebo Layoffs, Female Partners



(c) True Layoffs, Male Partners



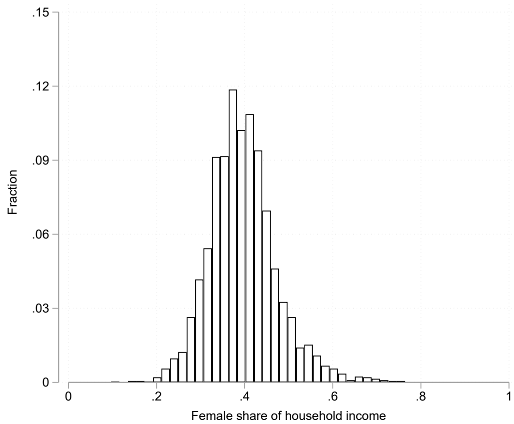
(d) Placebo Layoffs, Male Partners



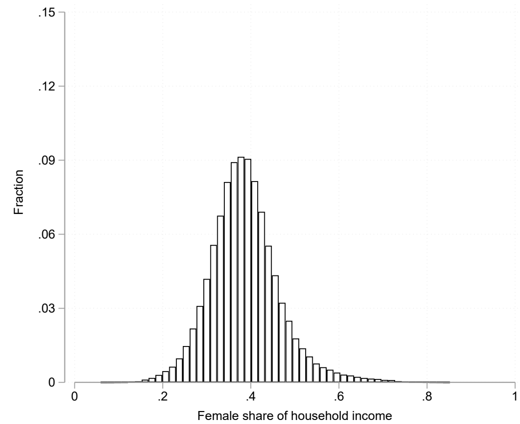
Notes: This figure displays histograms of age by gender for the partners of laid-off individuals sample in Sweden.

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

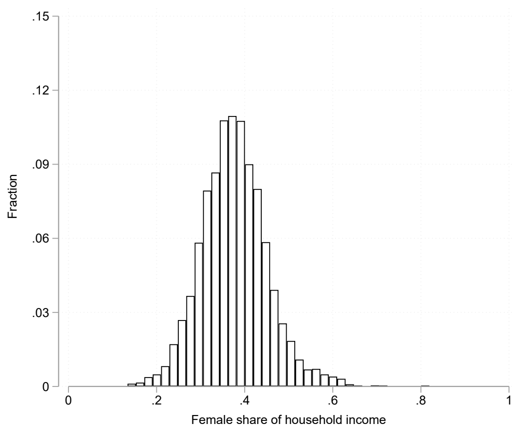
(a) True Layoffs, Women



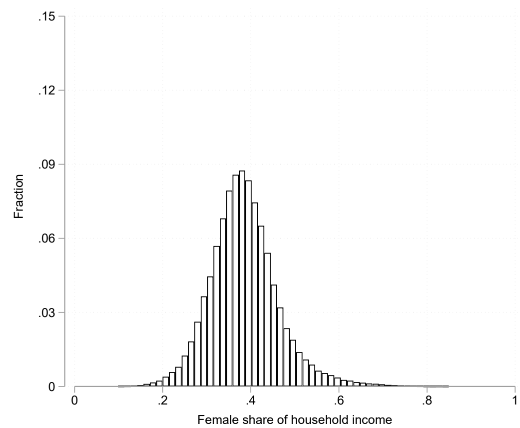
(b) Placebo Layoffs, Women



(c) True Layoffs, Men



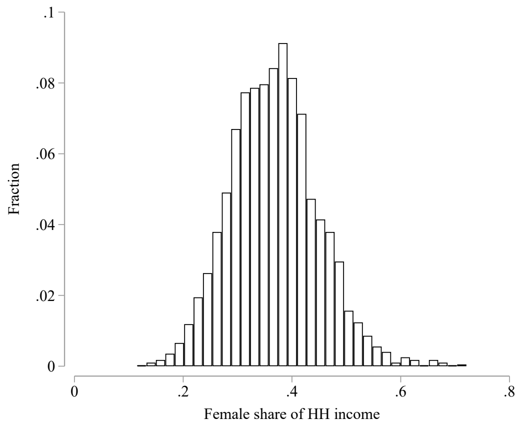
(d) Placebo Layoffs, Men



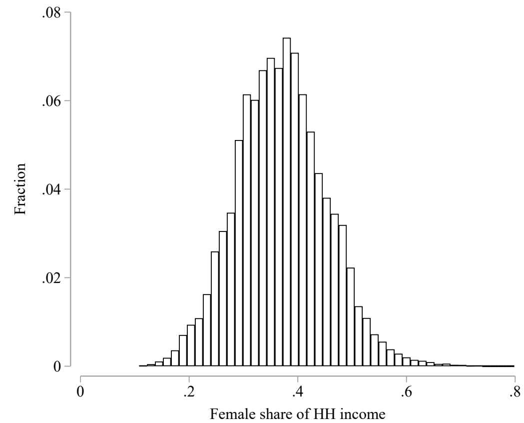
Notes: This figure displays histograms of predicted female share of household wage income by gender for the laid-off individuals sample in Sweden in $t = 4$. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study,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

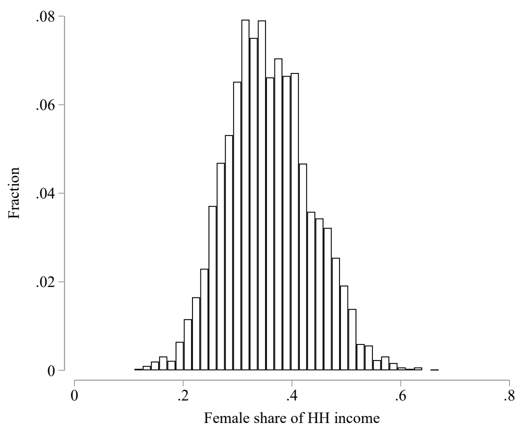
(a) True Layoffs, Women



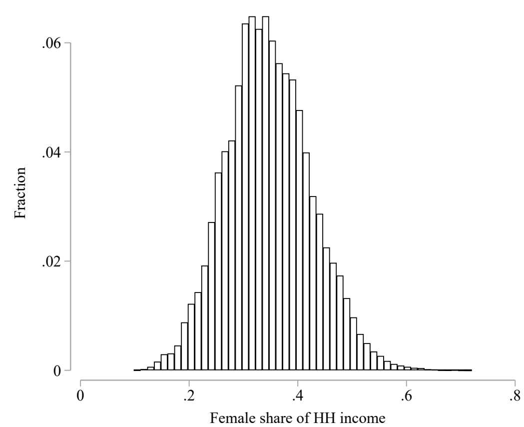
(b) Placebo Layoffs, Women



(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.

A.10 Restricted model parameters estimates

Table OA-2: Restricted Model Parameter Estimates

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Mean log income, men	3.49	3.18
Standard deviation of log income, men	0.77	0.61
Mean log income, women	2.58	2.54
Standard deviation of log income, women	0.90	0.73
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	-0.02	-0.09
Standard deviation in the returns to migration, σ_r	0.07	0.39
Mean household mobility cost, μ_c	7.87	-0.37
Relative weight on woman's income compared to man's income, β	1.00	1.00

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 for $\hat{s} < 0.5$ and $\hat{s} \geq 0.5$ reported in Table 4.

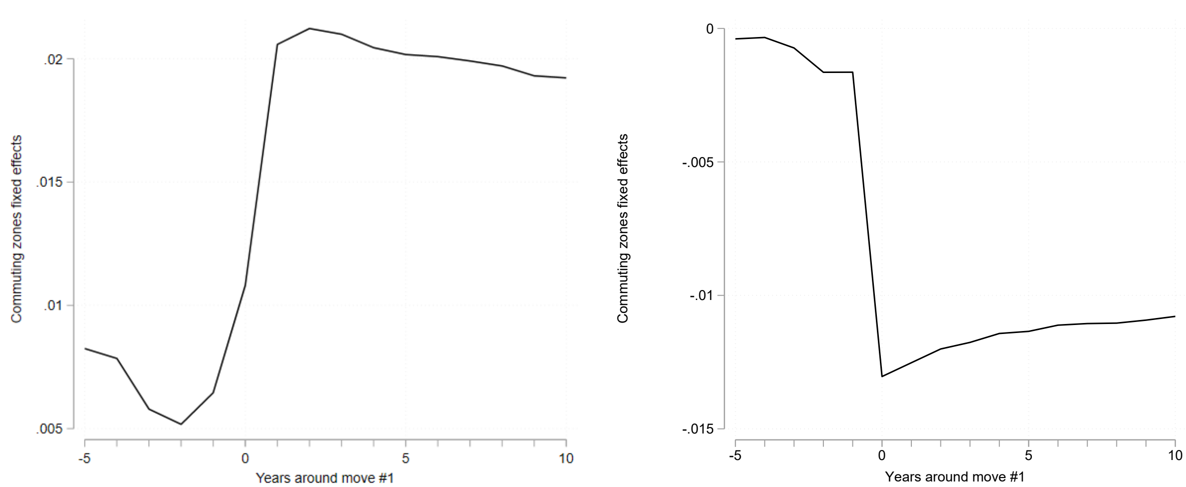
Table OA-3: Model Parameter Estimates from Two-step Estimation Approach

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Mean log income, men	3.49	3.18
Standard deviation of log income, men	0.77	0.61
Mean log income, women	2.58	2.54
Standard deviation of log income, women	0.90	0.73
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	0.04	-0.06
Standard deviation in the returns to migration, σ_r	0.03	0.21
Household mobility cost, c	7.75	3.63
Relative weight on woman's income compared to man's income, β	0.63	0.79

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 for $\hat{s} < 0.5$ and $\hat{s} \geq 0.5$ reported in Table 4.

Figure OA-13: Commuting Zone Fixed Effects

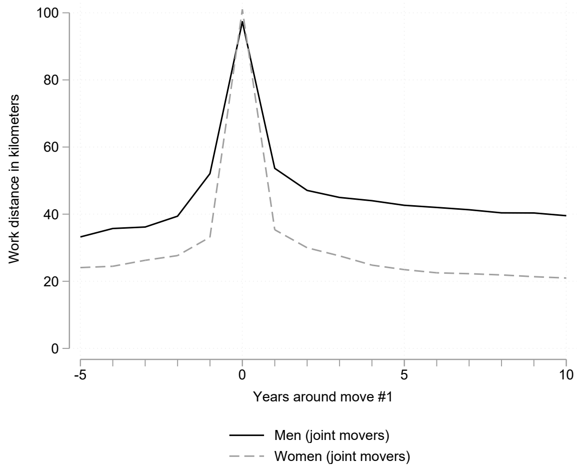
(a) Germany (b) Sweden



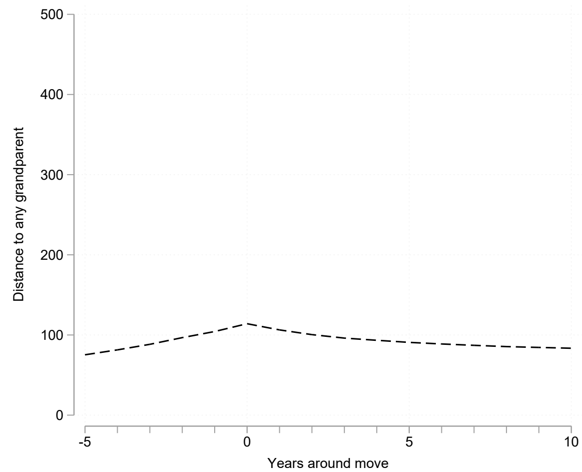
Notes: This figure displays the raw means of commuting zone fixed effects.

Figure OA-14: Amenities, Sweden

(a) Distance to work



(b) Distance to grandparent



Notes: This figure displays the distance to the job by gender and the distance to the closest grandparent for the movers sample.