Moving to Opportunity, Together[*]

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December 6, 2024

Abstract

Many couples face a trade-off between advancing one spouse's career or the other's. We study this trade-off using administrative data from Germany and Sweden. Using an event study approach, we find that when couples move across commuting zones, men's earnings increase more than women's. To distinguish between men's greater potential earnings and a gender norm that prioritizes men's careers, we examine how the patterns differ when the woman has higher potential earnings than her husband. We then estimate a model of household decision-making in which households can (and do) place more weight on income earned by the man.

JEL classification: J61, J16, R23

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

[*]This paper incorporates results from a previously-circulated working paper titled "Couples, Careers, and Spatial Mobility." We thank Connor Fogal, Eva Forslund, Daisy Lu, Angelo Marino, Isaac Norwich, Juliana Sánchez Ariza, and Nettie Silvernale for outstanding research assistance and Eric Chyn, Emir Kamenica, Henrik Kleven, Elio Nimier-David, and Alessandra Voena for helpful comments. We also thank the German Institute for Employment Research (IAB) and the IBF and Urban Lab at Uppsala University for generously providing the data and support and the Economics and Business and Public Policy Research Fund at the University of Chicago Booth School of Business for financial support.

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1 Introduction

A growing literature documents sizable within-household gender gaps in labor market participation and earnings.[1] This is at least in part attributable to men's careers being prioritized over women's. For example, as household demands increase, men continue to work in high-paying, time-demanding jobs while women pull back on their careers (Goldin 2021). It is unclear, though, whether men's careers are prioritized *because* they enter into high-paying occupations and therefore contribute more to household income, or whether they would be prioritized regardless of relative earnings. Although men do tend to have higher earnings potential than women, there is mounting evidence that gender norms influence household decision-making in favor of men (Bertrand et al. 2015; Bursztyn et al. 2017; Isaac 2024).

This paper uses joint location decisions to understand the extent to which household and labor market decisions are driven by gender differences in earnings potential or gender norms. We use administrative data from Germany and Sweden to first document the impact of moving on men's and women's earnings. In line with previous research, we find that women's earnings decline relative to men's following a cross-commuting zone move. We then propose a novel test to quantify how much of the earnings gap can be explained by differences in earnings versus a gender norm of couples prioritizing men's careers. Specifically, we focus on couples in which the man and woman have roughly equal predicted earnings. If couples are simply following the higher earner, we should see no earnings gap emerge among these couples following a move. Instead, we find that moves continue to favor men.

We use two methods to estimate how men's and women's earnings change following a move. We begin by establishing that couples are more likely to move when doing so benefits the man's career rather than the woman's. We use an event study design to trace the earnings trajectories of heterosexual couples who relocate and find that relocation disproportionately benefits men. While men's earnings increase by about 10% and 6% in Germany and Sweden over the first five years following the move, women experience almost no change in their earnings. The earnings gap arises through a combination of

[1] For example, women's earnings fall relative to men's following the birth of a child (Anderson et al. 2003; Budig and England 2001; Kleven et al. 2019a).

men experiencing an increase in wages and women spending less time in the labor market, particularly in the first year after the move. The gender gap in earnings following a move persists beyond five years and is present across all age groups but is most pronounced for couples who are in their 20s at the time of the move. Controlling for childbirth events and comparing couples who do and do not have children show that the earnings gap is not driven by couples deciding to have a child around the time of a move.

Moves are, of course, not exogenous events. We therefore complement the event-study analysis with a second causal research design. We use mass layoff events to test whether couples are more likely to move when the man is laid off than when the woman is. Mass layoffs generate plausibly exogenous job separations for both men and women in our sample and induce long-distance moves (Huttunen et al. 2018). In Germany, when the man is laid off, the couple's likelihood of relocating increases by roughly 50% (compared to a no-layoff counterfactual) and in Sweden it doubles, while the woman being laid off has no effect on relocation in either country.[2]

Having established that moves are made in favor of men's careers, we turn to assessing the relative importance of two main explanations for our findings. First, couples may move for men's careers because men, on average, have higher earnings potential. In this case, there is no gender bias; couples are simply following the career of the higher earner. Second, a gender norm may affect couples' decisions, meaning they put more weight on men's careers regardless of earnings differences. To distinguish between these mechanisms, we first provide descriptive evidence that gender norms correlate with the size of the post-move earnings gap. Prior work has shown that women of East German origin have higher labor force participation rates and return to work more quickly following the birth of a child (Rosenfeld et al. 2004; Boelmann et al. 2023). Studies have also shown that men's childhood exposure to working women influences their wives' labor supply (Fernandez et al. 2004). We look at couples of East and West German descent who are currently located within West Germany. We find that among couples who relocate within West Germany, the post-move gender gap in earnings is smaller when at least one spouse is of East German origin. The gap is absent among couples in which the man grew up in East Germany.

[2]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. 2023).

To more formally test these two explanations, we develop a model of household decision-making in which households can place more weight on income earned by the man than by the woman, as in Foged (2016). An intuitive prediction of the model is that with standard joint income maximization — in which equal weight is put on each person's income — 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 reversed when the woman is the primary breadwinner. We find that in both countries, 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. However, they do not explain all of the gap, as can be seen most clearly by examining the couples in which the woman has the higher potential earnings. Gender-blind income maximization would predict that women benefit more than men from moving among these couples. We instead find that the gender gap closes but women do not benefit much more than men in Sweden, while in Germany men continue to benefit more than women even though the woman has higher potential earnings.

Using these reduced-form results as empirical moments, we estimate the model parameters separately for each country using simulated method of moments. Specifically, we estimate a parameter, β, that is the weight couples put on women's earnings relative to men's. If $\hat{\beta} < 1$, couples value women's income at a fraction of how they value men's income. If couples put equal weight on the earnings of men and women, we would estimate $\hat{\beta} = 1$. We test and reject a gender-blind ($\hat{\beta} = 1$) model of decision-making in both countries, with larger deviations from this 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. As an additional implication of our model-based estimates, we simulate a model of the child penalty by extending the model in Andresen and Nix (2022) to allow households to put less weight on income earned by the woman, and we calibrate the relative weight on income in each country using our model-based estimates. We show that gender norms can quantitatively account for a large share of the estimated female child penalty in both countries.

Interpreting our model estimates as evidence of a gender norm relies on the assumption that men and women have the same job opportunities and expected returns to migration, conditional on predicted earnings. This might be violated if women tend to be in occupations with lower returns to moving. However, we find similar results when we re-weight the sample so that the occupational distribution is the same for men and women. It is also possible that women have a preference to accommodate their husbands' preference to be the primary breadwinner, which we consider to be part of a gender norm. What our findings are able to rule out is that the gender gap is driven by women having a stronger preference for, say, leisure, given the differences between women with East and West German husbands.

The final part of the paper considers alternative explanations for the gender gap. We consider the possibility that women anticipate leaving the labor market upon having children, that there are geographic differences in job opportunities by gender, and that women are compensated during moves in the form of non-wage amenities. We find little evidence that any of these mechanisms is driving the results. 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 two lines of research. First and most importantly, we contribute to the literature seeking to understand how gender norms affect household decision-making (Bertrand et al. 2015; Boelmann et al. 2023). A large literature has documented gender gaps in labor market outcomes, with a number of papers highlighting the importance of intra-household decision-making in explaining these gaps.[3] Few papers have been able

[3]Several papers have found that "child penalties" play an important role in the earnings 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 experience lower wage growth than men when changing jobs (Loprest 1992) and show a lower willingness to commute (Le Barbanchon et al. 2020), likely because of family commitments.

to understand why decisions within the household typically benefit men's careers over women's. We are able to make progress by focusing on close-earning spouses, which shuts down the channel of men having, on average, higher earning potential. This allows us to assess how much of the gender gap in earnings that emerges following a move is due to a gender norm.

Second, our paper contributes to an older, largely theoretical literature on joint migration decisions as well as a new, empirical literature documenting gender differences in the returns to joint moves. A seminal contribution on so-called tied movers is Mincer (1978), who modeled joint migration decisions in two-earner households. In addition, several early empirical papers established that joint moves typically benefit men more than women (Duncan and Perrucci 1976; Sandell 1977; Spitze 1984; LeClere and McLaughlin 1997; Cooke 2003; Nivalainen 2004; McKinnish 2008; Cooke et al. 2009; Rabe 2009; Tenn 2010; Blackburn 2010a,b). More recently, studies have employed modern empirical methods to investigate particular aspects of the tied mover phenomenon or the returns to moving for specific subpopulations. Fadlon et al. (2022) examine male and female medical graduates' internship choices in Denmark, finding that women are less likely to relocate from their first labor market, which contributes to their lower long-run earnings. Burke and Miller (2018) use military spouses to estimate the impact of an exogenous move on the spouse's labor market outcomes and find that moves reduce the spouse's earnings. Johnson (2021) studies US couples in which at least one spouse has a state-specific occupational license and finds that the husband's license status is more influential in the migration decision than the wife's status. Venator (2024) examines different migration policies, such as unemployment insurance for trailing spouses, joint offers, and migration subsidies, and finds that these policies may lead to positive effects on wives' labor market outcomes.[4] By using administrative data from two countries, we are able to contribute to this literature by showing how men's and women's earnings change following a move for the entire population (or a 25% random sample of the population), rather than for specific occupations or industries. The

[4]Papers analyzing how couples make location decisions include Guler et al. (2012), who investigate reservation wage strategies of couples. Using a spatial directed search model, Foerster and Ulbricht (2023) find that co-location frictions discourage migration and affect women more than men. With a dynamic search model, Gemici (2023) investigates optimal household location choices and affirms that they favor the partner with higher earnings potential. Earlier papers documented 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).

rich, linked administrative data also allow us to test whether the gender gaps are driven by differences in occupation choice, the desire to be closer to parents, or the choice of when to have children. Finally, we are able to establish causality using our sample of laid-off individuals.

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 we present the reduced-form results in section 4. We assess the two main explanations for our findings (earnings versus norms) in Section 5. This includes first comparing East and West German couples, and then developing a model of household decision-making. We present additional empirical results motivated by the model, and quantify the role of gender norms in explaining the empirical patterns. We explore alternative mechanisms in section 6, and section 7 concludes.

2 Data

We use administrative data from Sweden and Germany to test whether, within heterosexual couples, moves disproportionately benefit men and, if so, whether this is due to earnings differences or gender norms. These datasets have several valuable, complementary features. First, in each dataset, we have geographic information on the place of residence for each spouse, which is necessary to investigate the effects of joint moves.[5] Second, the data include detailed labor market histories of both spouses, allowing us to 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. Finally, the data allow for much larger samples than longitudinal surveys.

[5]Throughout the paper, we often refer to spouses. However, in Sweden, we identify couples regardless of whether they are married.

2.1 German Data

For Germany, we use a 25% random sample of all married couples that can be identified in the administrative database Integrated Employment Biographies (IEB) with the couple identifier generated by Baechmann et al. (2021).[6] The IEB includes all employees subject to social security (which excludes civil servants and self-employed), everyone receiving unemployment benefits, and those who have been registered as searching for a job. Married couples were identified by Baechmann et al. (2021) using the method of Goldschmidt et al. (2017): for two people to be matched as a couple, they must live in the same geocoded building, have a matching surname (e.g., the woman takes her husband's surname or uses it in a hyphenated/double surname, or vice versa), be opposite sexes, have an age difference less than 15 years, and live in a building with no other people with the same name with records in the data. The identification of couples was done every year on June 30 from 2001 to 2014. Therefore, in a particular year, two people are only identified as a couple if both spouses have a record in the IEB on June 30. Once we have identified a couple pre-move, we keep both partners in our sample even if one partner drops out of the labor force, or they separate.[7] The surname criterion means we may miss couples with particularly progressive gender norms. That said, sharing a common name is still widespread in Germany: for couples who married in 1996 (2016), 91% (87%) share a common name (GFDS 2018).[8]

The algorithm produces few false positives (i.e., pairs who are incorrectly identified as couples even though they are not). A larger limitation is that the algorithm only identifies one third of married couples living in Germany and who are attached to the labor market (Goldschmidt et al. 2017). This would be particularly concerning if selection into being labeled a couple was based on gender norms (i.e., if it were mainly because of shared surnames). However, the main reason for missing couples is that for a large number of individuals in the IEB, no exact building geocodes are assigned (Baechmann et al. 2021).

[6] We use version 16.01 of the IEB. The IEB is held by the Institute for Employment Research (IAB).

[7] This means that we miss couples in which the woman or man is never in the labor force during our sample period. If the person is ever in the labor force or receives UI benefits, the couple is included; a person with no record in a given year is kept in the data with zero earnings.

[8] Later, we put a lower bound on the role of gender norms by assuming that the 13% of couples who do not share a last name make gender-blind household decisions. See Section 5.2.4

In addition, the algorithm identifies fewer couples living in large buildings. There are no direct identifiers in German administrative employment data that enable the linking of family members, so we cannot identify unmarried couples or singles (in the latter case because of the many couples not identified by the algorithm).

The IEB data includes employment spells spanning 1975 to 2021, with information on earnings, occupation, and other job details.[9] The earnings data are very accurate, as the employer has to report earnings for social security purposes. However, wages are reported only up to the social security contribution ceiling, so we impute right-censored wages.[10] The IEB also includes every period of receiving unemployment benefits and the amount of benefits, as well as information on periods of job search and participation in subsidized employment and training programs. The data also include personal characteristics such as year of birth and education. The data administrators can link employment spells to establishments, and, from these links, they have created indicators for mass layoffs.[11]

2.2 Swedish Data

We use individual-level administrative data from Sweden from the GEO-Sweden database, which covers the entire Swedish population between 1990 and 2017. The GEO-Sweden database has precise geo-data on residential and workplace addresses, including residential building IDs and 100×100 meter home and workplace geo-coordinates.

Couples are assigned a family ID if they are married or have a joint child. In addition, through origin and destination residential building IDs, we can identify joint moves of cohabiting couples regardless of their marital or parental status. We follow the Statistics Sweden definition of a cohabiting couple: two people of opposite sexes who are no more than 15 years apart in age, are not related, and are the only two people residing in the same building who meet the other criteria to be matched together. In our main analysis, we use both married and cohabiting couples for Sweden.

[9] Data for East Germany is available beginning in 1992.

[10] 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).

[11] We sometimes use the term 'firm' for simplicity, but note that, for Germany, we can only identify establishments and are unable to link them to firms.

Similar to the German data, the Swedish data contains information on earnings, unemployment benefit receipts, and education from the Longitudinal Integrated Database for Health Insurance and Labor Market Studies (LISA). An advantage of the Swedish data is that we also have detailed information on an individual's college major, which we use when constructing predicted earnings, but we do not have occupation data. There is information on firms and establishments for all individuals, allowing us to identify mass layoff events. We do not, however, have information on labor market participation or hours worked. We follow the convention in the Swedish context and measure non-employment as a yearly wage income lower than 2 "price base amounts" (*prisbasbelopp*), corresponding to around €8,000 in 2017.[12] In addition, the Swedish data link parents and children, so we observe the year of birth for all of an individual's children.

2.3 Moving Across Commuting Zones

To focus on couples who change local labor markets when they relocate, we study moves across commuting zones. For Germany, Kosfeld and Werner (2012) define commuting zones as districts connected through high commuter flows and identify 141 commuting zones. For Sweden, we use Statistics Sweden's concept of *functional analysis region* to define 60 commuting zones (see Figure 1).[13] 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 and the other follows in $t + 1$.

2.4 Sample and Variable Definition and Descriptive Statistics

2.4.1 Movers Sample

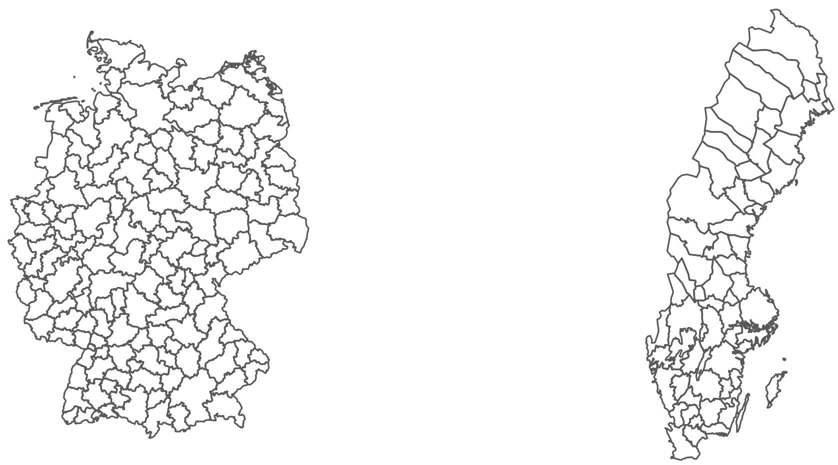
Our main sample is couples who move together between 1995 and 2007 in Sweden and between 2001 and 2011 in Germany. During the observation period, a few couples experienced multiple long-distance moves. We consider only their first move, because future outcomes may be influenced by the first move.

[12] The "price base amount" (*prisbasbelopp*) is an annually adjusted measure used to calculate social benefits, ensuring they keep pace with inflation and changes in the cost of living.

[13] More details can be found 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). In Sweden, commuting zones are defined by the Swedish Agency for Growth Policy Analysis.

We restrict the data to couples in which at least one spouse was between age 25 and 45 at the time of the move. We make this restriction because those moving at an older age are more likely to be doing so for non-work reasons. Couple-years in which one spouse is above 60 or below 18 are excluded. We also exclude couples in which at least one person is a student in the two years prior to the move so that income changes following the move are not due to initial labor market entry.[14] In the Swedish data, we use the receipt of student benefits to identify student status. In the German data, we use enrollment in firm-based education (e.g., apprentice, intern) but we do not have information on college enrollment.

We construct a panel that includes all couples whom we observe for at least the 2 years before the move through the 4 years after the move (i.e., a partially balanced panel).[15] Our final sample consists of $19,953$ moving couples in Germany and $47,313$ couples in Sweden.

[14]We also drop couple-years before the move (earlier than $t = -2$) when one or both members of the couple is a student.

[15]This balanced-panel rule, combined with the years for which the administrative data are available, determines the range of move years included in our analysis. Individuals with no record in a given year, likely due to being out of the labor force, are included in the panel with zero labor earnings.

Table 1 presents descriptive statistics for the German and Swedish mover samples. There are notable baseline gender gaps. In the German sample, men are more likely to have a college education than women. In both countries, men's earnings and employment rates are higher than women's, with a larger gender gap in Germany than Sweden. Roughly 65% of couples in our sample have a child. We will both control for having a child in our analysis and look at heterogeneity by whether the couple has a child.

2.4.2 Layoff Sample

For the layoff analysis, we consider displacements from mass layoffs between 2001 and 2006 in Germany and between 1995 and 2007 in Sweden. In the German data, a mass layoff is defined as an establishment with at least 50 employees experiencing a decline in employment of more than 30%.[16] The Swedish layoff sample is constructed using the same criteria, except that no more than 30% of the outflow is to one establishment. Our samples consist of those workers experiencing a mass layoff who had at least one year of tenure and earned at least €8,000 in the year before the mass layoff (to reduce the likelihood of including temporary workers).[17]

Because couples are included in this analysis regardless of whether they move, we can no longer identify couples in Sweden through joint moves from one building to another. Couples are identified through their family ID, which encompasses married couples and couples with a child. In Germany (where we do not have access to the building IDs), we continue to use the sample of couples that were identified for us by the data administrators.

Appendix Tables A-1 and A-2 present descriptive statistics for the layoffs sample. The columns labeled "Male Layoff" show the characteristics of the laid off man and his spouse while the "Layoff Women" columns show the same but for the laid off woman and her spouse. By construction, laid off individuals are all employed in the year before the layoff. The fraction of couples with at least one child is especially high in Sweden since cohabiting couples are identified and included in the layoff sample based on the presence of a child.

[16]The definition also requires that the establishment had no increase of 30% of employees or more in the two preceding years and no more than 20% of the outflow is to one particular establishment (which might indicate an acquisition or spinoff). This definition is similar to Schmieder et al. (2023) and other papers using German data.

[17]Further restrictions are (1) the pair is identified as a couple before the layoff, (2) the laid-off worker does not return to the establishment in the next five years, (3) both spouses are not laid off at the same time, (4) it is the person's first layoff we observe, and (5) at least one spouse is between age 25 and 45.

Table 1: Summary Statistics for Movers Sample - Germany and Sweden

	Germany		Sweden	
	Men	Women	Men	Women
Age	36.27	33.92	34.97	32.78
	(6.07)	(6.02)	(6.69)	(6.33)
Compulsory schooling	0.01	0.02	0.13	0.13
	(0.10)	(0.14)	(0.34)	(0.33)
High school	0.04	0.06	0.48	0.44
	(0.20)	(0.24)	(0.50)	(0.50)
Vocational training	0.61	0.70	0.07	0.04
	(0.49)	(0.46)	(0.26)	(0.21)
Some college			0.07	0.12
			(0.26)	(0.32)
College degree	0.34	0.21	0.25	0.27
	(0.47)	(0.41)	(0.43)	(0.44)
Wage income (1000s EUR)	46.46	20.40	28.50	16.30
	(39.91)	(22.31)	(19.65)	(14.09)
Employed	0.89	0.80	0.88	0.83
	(0.31)	(0.40)	(0.32)	(0.37)
UI benefits (1000s EUR)	0.57	0.35	0.91	0.99
	(2.00)	(1.32)	(2.72)	(2.60)
Days receiving UI benefits (per year)	18.93	18.71	25.16	25.35
	(62.87)	(65.23)	(66.44)	(64.02)
At least 1 child	0.65	0.65	0.66	0.66
	(0.48)	(0.48)	(0.47)	(0.47)
Non-native	0.07	0.08	0.15	0.16
	(0.26)	(0.27)	(0.36)	(0.36)
Observations	19953	19953	47313	47313

Notes: This table displays means and standard deviations (in parentheses) for the listed variables in the year before a couple moves ($t-1$) in Germany and in Sweden. Data on whether an individual has completed some college is not available for Germany. Wage income and other benefits are measured in 2017 Euros.

The male layoff and female layoff couples differ in their characteristics. This is unsurprising because, to be laid off, an individual needs to work at an establishment with at least 50 employees and meet other criteria, and couples in which the man meets these criteria differ from couples in which the woman meets them. To eliminate these compositional differences when we compare men's and women's layoffs, we include a non-layoff comparison group in our analysis. The comparison group for the male-layoff sample are couples in which the man meets the establishment size, job tenure, and minimum earnings criteria that apply to layoffs. The comparison group for the female-layoff sample are couples in which the woman meets the criteria. We assign a placebo age at layoff based on the age distribution among actually laid-off workers in the person's gender-birth-cohort-education cell.[18] This age at layoff then maps to a layoff year, which we use to define the placebo group's "layoff" timing. The "True Layoff" and "Placebo Layoff" columns in Appendix Tables A-1 and A-2 compare the characteristics of laid off workers to the placebo groups. Placebo workers are more likely to have a university education and have higher earnings.

3 Empirical Strategy

3.1 Event-Study Analysis of the Effects of Moves

We use event studies to estimate the impact of a move on men's and women's labor market outcomes. 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 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 the anticipated effects of moving: Are couples as likely to move for anticipated increases to the woman's earnings as to the man's?

[18] This procedure is similar to the approach used by Kleven et al. (2019a) for assigning placebo births to childless couples.

Our main estimation equation is:

$$Y_{ist}^{g} = \sum_{j \neq -1} \alpha_j^g \times \mathbb{1}[j = t] + \sum_{p} \beta_p^g \times \mathbb{1}[p = educ_{is}] + \gamma^g \times age_{is} + \delta^g \times age_{is}^2$$
$$+ \sum_{y} \nu_y^g \times \mathbb{1}[s = y] + \sum_{m \neq -1} \tau_m^g \times \mathbb{1}[m = t_{ch}] + \theta^g NoChild_{ist} + \epsilon_{ist}^g \quad (1)$$

which we estimate separately by gender g. 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 control for education level ($educ$), age (age), age squared (age^2), as well as calendar year indicators ($y = s$).[19] Standard errors are clustered at the individual level.

There are two main threats to this identification strategy. First, couples might move in response to events that impact both the decision to move and individuals' earnings. 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 include event-time indicators for the couple's first joint child ($m = t_{ch}$), and an indicator for having no children, $NoChild_{ist}$.[20]

Second, men and women may have different job opportunities across commuting zones. Such differences would affect the interpretation of our results. We address this possibility in Section 6 by re-weighting men and women to have the same occupational distribution, among other robustness checks.

[19] For Sweden, there are five education levels: compulsory schooling, high school, vocational training, some college, and college. For Germany, there are four: compulsory schooling, high school, vocational training, and college. We find similar results if we replace the quadratic in age with a full set of age fixed effects (Figure A-1). We use the quadratic in age due to the smaller sample sizes when we split the sample by the predicted female share of household income.

[20] Results are similar if we include include event-time indicators for each of the couple's first three children or exclude child controls entirely (Figure A-1).

3.2 Effect of Layoffs on Moving

We use mass layoff events to examine whether couples are more likely to relocate following a job separation of the man as opposed to the woman. The sample restrictions we use to zoom in on laid off individuals (e.g., having a tenure of at least one year) create sample composition differences between male and female layoffs. Thus, we use a control group for male layoffs of couples without a layoff where the man fulfills the same restrictions, and the same for female layoffs (see section 2.4.2).

We then estimate the following equation:

$$M_i = \alpha \times \text{Male Layoff}_i + \beta \times \text{Female Layoff}_i + \gamma \times \text{Male Layoff or Male Placebo}_i + X_i + \epsilon_i, \tag{2}$$

where M_i is a dummy indicating whether couple i lives in a different CZ in year t or $t+1$, and X_i is a vector of controls (a constant term, the age of both spouses, and a dummy for the CZ at layoff). The effect of a male layoff relative to a placebo male layoff is α, while the effect of a female layoff relative to a placebo female layoff is β. The key statistical test is whether $\alpha = \beta$.

4 Results

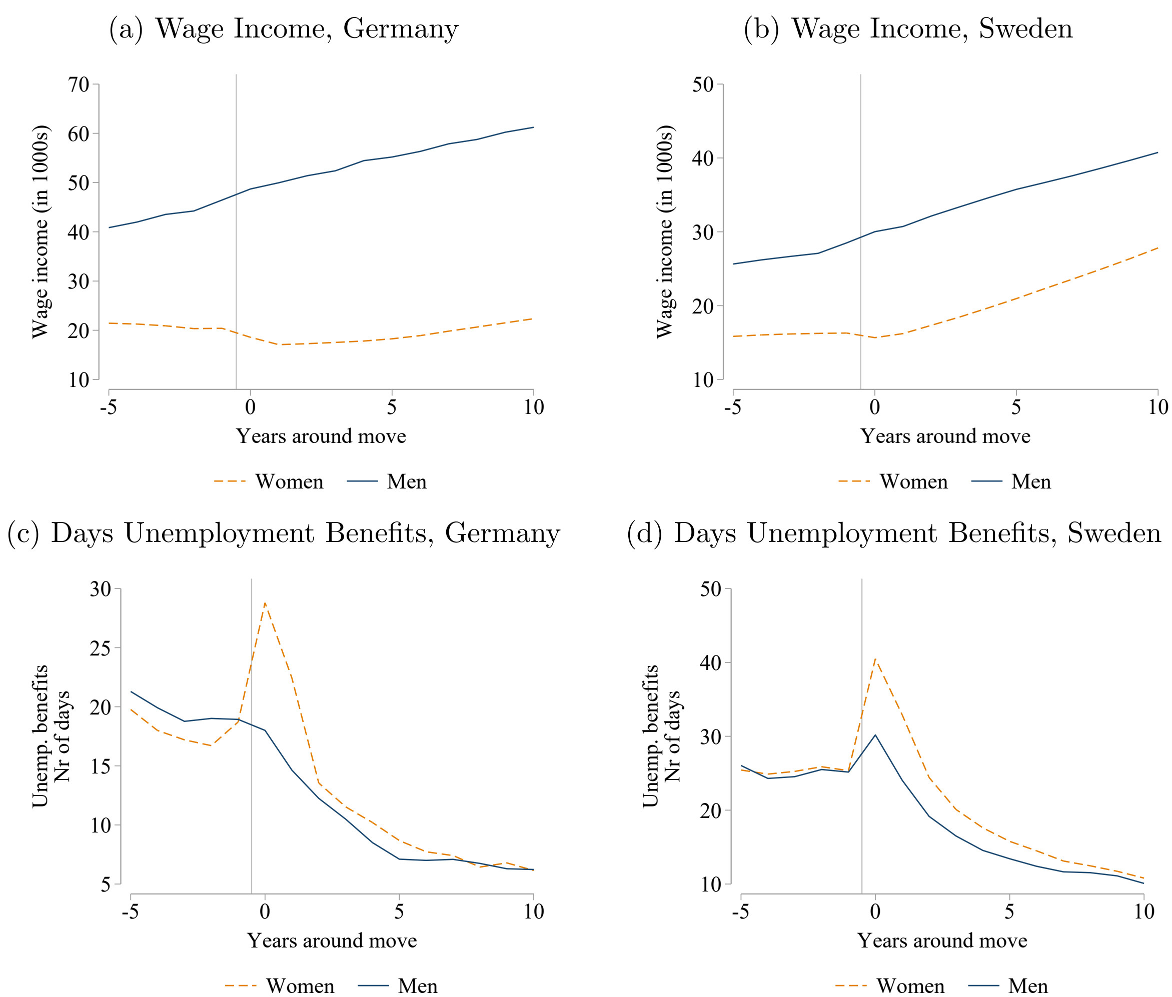
4.1 Earnings and Employment Effects of Moving

We begin by exploring the impact of moving on men's and women's earnings and employment. We first plot 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 earnings are relatively flat prior to the move in year 0, after which men's earnings steadily increases. For both countries, we see a slight dip in women's earnings around the time of a move followed by income growth.

These moves appear to occur in part following a period of unemployment. Panel (c) and (d) show that men and women receive fewer days of unemployment benefits following a move, however, there is a spike in benefit collection for women in the year of and the year after a move suggesting that part of women move without a job-offer at hand. Balgova

(2022) shows that such moves are associated with lower wages and a higher probability of unemployment. In both countries, spouses can, under some conditions, collect unemployment benefits if they have to move for their partner's career. These results provide initial evidence that these moves may be for the benefit of men's careers.

Figure 2: Relationship between Moving and Wage Income and Employment



(a) Wage Income, Germany

(b) Wage Income, Sweden

(c) Days Unemployment Benefits, Germany

(d) Days Unemployment Benefits, Sweden

Notes: This figure displays the average wage income (panels (a) and (b)) and the average number of days in which an individual received unemployment benefits (panels (c) and (d)) by gender in Sweden and in Germany, before and after a cross-CZ move. Wage income is measured in 2017 Euros.

Turning to our main estimation strategy, we compare the labor market outcomes for men and women who move across commuting zones, while controlling for age, education, calendar year, and child event-time indicators. The coefficients from estimating equation 1 are plotted relative to the average of the outcome variable in the year before the move

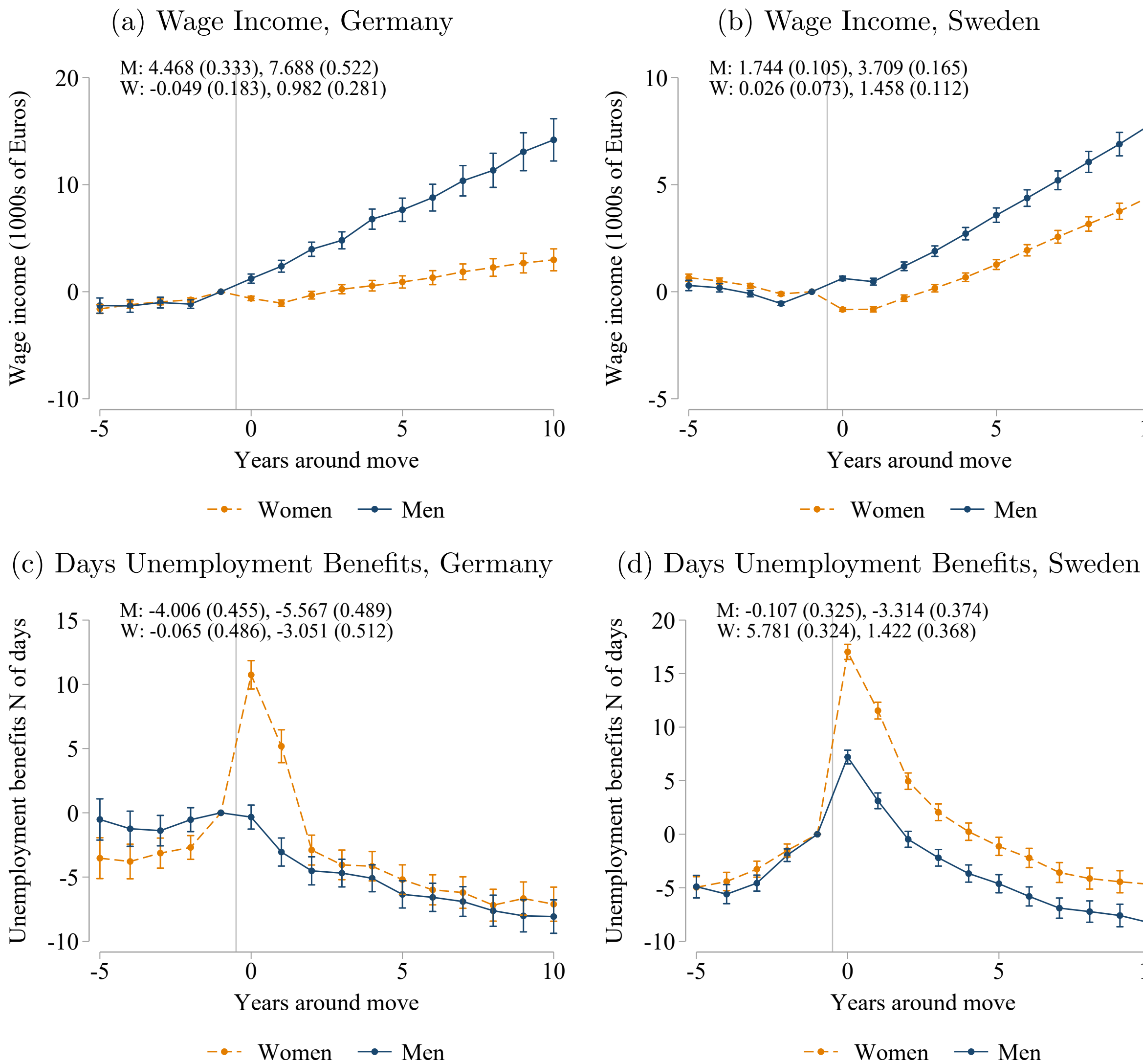
($t = -1$) in Figure 3. In both Germany and Sweden, a gap between men's and women's earnings emerges the year of the move and steadily grows over time. Over the first five years after a move, men are earning about €4,500 and €1,700 more than they were in the year prior to the move, while women's earnings have not increased in either country. This corresponds to women's share of the couple's earnings falling by 2.5 percentage points in Germany and 1.1 percentage points in Sweden, as shown in Appendix Figure A-2.[21]

To investigate whether spouses' earnings responses are driven by changes in employment or in wages, panels (c) and (d) of Figure 3 show the effect of moving on the number of days an individual received unemployment benefits. In Germany, some couples appear to be moving in response to the man's unemployment: The average number of days that men collect unemployment days falls by 4 days per year within five years of a move. In contrast, women experience a spike in unemployment in the year of the move and immediately following the move, suggesting that women did not have a job lined up when the couple moved. As shown in Appendix Figure A-4, men spend 17 more days employed per year five years after a move relative to the year before the move. Women, on the other hand, are employed three fewer days per year. In Sweden, both men's and women's receipt of unemployment benefits increase in the year of the move, but by significantly more for women. Appendix Figure A-4 shows the effect of a move on other employment measures for Sweden, which display similar patterns.

The results in Figure 3 indicate that relocation increases wage earnings of men more than women in absolute terms. Figure 4 shows the results in proportional terms. Here we normalize the event study estimates by the average income of men and women in each country in the year prior to the move. There is a 9.8 percentage point earnings gap in Germany and a 5.9 percentage point gap in Sweden when averaging over the five years following a move. Interestingly, in both countries men and women experience long-run earnings increases, even though men experience greater earnings growth in both absolute and percentage terms. The fact that average earnings increase significantly for both mem-

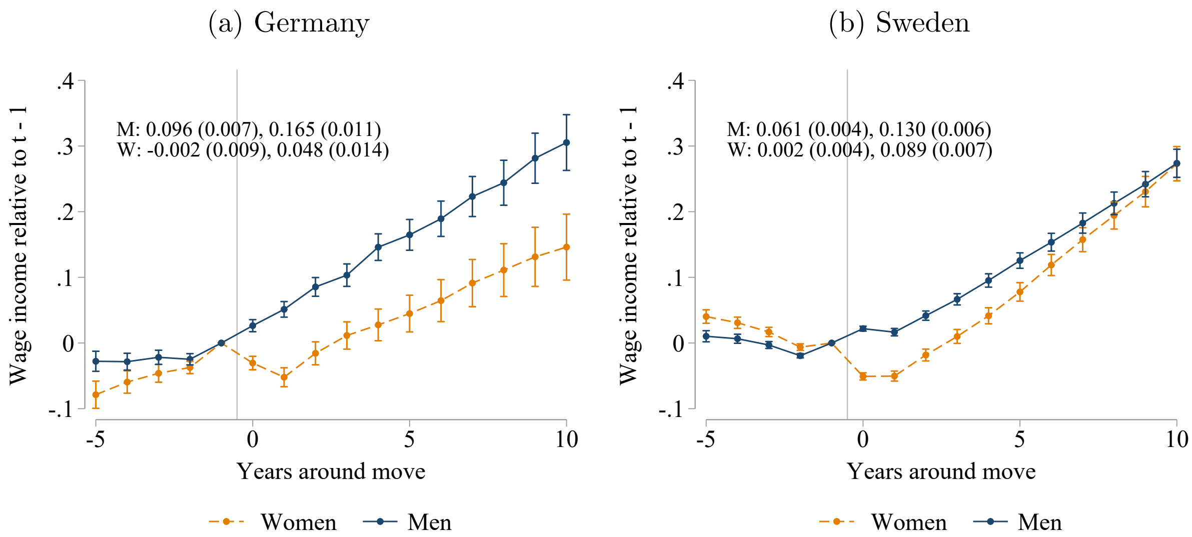
[21] In Appendix Figure A-3 we test whether the returns to moving vary with age. We define age groups (20–29, 30–39, and 40–50) based on the average age of the spouses in pre-move year $t - 1$ and plot the event time coefficients separately for these groups. We see gender differences in the returns to moving for all age groups, but they are smallest in the oldest age group, where men's returns are relatively low.

Figure 3: Impact of Move on Wage Income 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 left corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W).

Figure 4: Proportional Impact of Move on Wage Income



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

bers of the household is consistent with high average returns to moving, which could be rationalized by large migration costs (that prevent households from taking advantage of opportunities with only modest returns).[22] Therefore, women are not being made worse off by the move, but the moves seem to be consistently in favor of the man's career.

Robustness to staggered difference-in-differences concerns

We do not use a never-treated control group as there is selection into moving. As such, we are using both not-yet-treated and already-treated units as controls, meaning our estimates may be contaminated by treatment effects in later or earlier periods. To account for this possibility, we use the estimator proposed in Sun and Abraham (2021). The coefficients, shown in Appendix Figure A-5 are largely unchanged.

[22]Other evidence of high average returns to moving includes Deryugina et al. (2018) and Kennan and Walker (2011). More recently, Card et al. (2023) estimate the causal effects of CZs on earnings using cross-CZ movers in the US. Using their results, we estimate an average return to moving across CZs of 3-4 percent five quarters after the move, which is broadly similar to our event study results in Germany and Sweden at the same time horizon.

4.2 Effect of a Mass Layoff on Likelihood of Moving

The event study results show that a significant earnings gap emerges following a joint move, which is consistent with couples being more likely to relocate if it advances the man's rather than the woman's career. In this section, we present a second test of whether moves are prompted more by men's career needs. We use mass layoff events to test whether couples are equally likely to move following men's and women's layoffs.

Our sample comprises about 10,000 layoffs in Germany (6,000 among men and 4,000 among women) and 15,000 layoffs in Sweden (8,000 among men and 7,000 among women), using the layoff definition and sample construction described in section 2.4.2.[23] The analysis also uses a comparison group of "placebo layoff" couples, as described earlier.

Table 2 shows estimates for the impact of a layoff on the likelihood that a couple moves (see equation 2). We regress an indicator for a couple moving in the year of or the year after a mass layoff on an indicator for the man (woman) being laid off. The reported coefficients are relative to the "effect" of a gender-specific placebo layoff.

Column 1 shows that in Germany, a man's layoff increases the probability of moving by 0.39 percentage points relative to a baseline moving rate of 0.71%. A woman being laid off increases the likelihood of moving by only 0.03 percentage points. We include age and commuting zone fixed effects in columns 2 and 3. The gap in moving rates remains although we can no longer reject equality of the effects of a male and female layoff.

Columns 4 to 6 show that, in Sweden, the likelihood of moving roughly doubles when a man is laid off, increasing by 1.3 to 1.4 percentage points from a baseline moving rate of 1.46%. In contrast, the likelihood of moving is unchanged when a woman is laid off.[24] We can reject equality of the moving response to a male and female layoff. Of course, finding a new job locally after a layoff may be easier in some occupations than others, and there might be gender differences in occupations along this dimension. We address this possibility in Section 6 where we re-weight our samples so that men and women have the same distribution of occupations.

[23] We show descriptively how earnings and employment change following a mass layoff in Appendix Figure A-6. Wage income drops sharply for both laid-off men and women. In Germany, men's income recovers to its $t = -1$ level about five years after the layoff, whereas the recovery is slower for women. In Sweden, wage income recovers for both genders after a year.

[24] In Norway, the effects of male and female layoffs on relocation are similar to each other (Huttunen et al. 2018).

Table 2: Impact of Layoffs on Moving Probability

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Male Spouse Laid Off	0.39	0.30	0.32	1.31	1.42	1.40
	(0.13)	(0.14)	(0.14)	(0.19)	(0.19)	(0.19)
Female Spouse Laid Off	0.03	0.05	0.08	-0.08	0.03	0.02
	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)
Age FE		✓	✓		✓	✓
CZ FE			✓			✓
N (Men Laid Off)	6177	6177	6177	8050	8050	8050
N (Women Laid Off)	4145	4145	4145	6767	6767	6767
Mean	0.71	0.71	0.71	1.46	1.46	1.46
M=W p-value	0.046	0.162	0.190	<0.001	<0.001	<0.001
Observations	155822	155822	155822	263563	263563	263563

Notes: This table displays point estimates and robust standard errors (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. All points estimates and standard errors are multiplied by 100.

5 Earnings vs. Norms

Our analysis suggests that moves benefit men's careers more than women's careers. In this section, we distinguish between two main mechanisms: (1) couples maximize household earnings and prioritize the man's career because men tend to have higher earnings, or (2) couples abide by a gender norm that prioritizes men's career advancement. We begin by exploiting geographic differences in gender norms within Germany to provide suggestive evidence that a norm is driving behavior. We then turn to our main test of gender norms. We develop and estimate a model of household decision-making to quantify, under a set of assumptions, how much of the gender gap is driven by earnings differences versus norms. In the following section, we then test for alternative explanations, including anticipation of a child penalty and occupational differences between men and women.

5.1 Evidence of Norms: East and West Germany

To test whether a gender norm is driving our results, we use couples' family origins as a source of variation in gender norms. 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 (Trappe 1996). Existing research has shown that whether women grow up in East or West Germany influences labor supply decisions (Boelmann et al. 2023; Trappe 1996). This provides us with an ideal natural experiment in which we can compare couples currently living in West Germany, and who therefore face similar institutions, but who are of either East or West German background.

We follow Boelmann et al. (2023) and use the location of an individual's first job as a proxy for West German or East German origins. We focus on couples currently living in West Germany and compare couples in which at least one spouse is of East German origin with couples in which neither is of East German origin. We restrict our sample of West German couples to those in which at least one partner has moved before, since the East German individuals must have moved at least once to be in West Germany.

Figure 5 plots the coefficients from estimating equation 1 for couples in which at least one spouse is of East German origin (panel a) and for couples in which neither spouse is of East German origin (panel b). The gender gap in earnings among couples in which neither spouse is from East Germany is large, with a long-run earnings gap of roughly €7000. The gap is substantially smaller (€3100) among couples that have at least one spouse from East Germany. Given the research showing that men who are exposed to a working mother have more liberal gender attitudes (Fernandez et al. 2004), we further split the sample based on whether the man is of East German origin (panels c and d). The gender gap closes when the man is of East German origin but is €7000 when the man is of West German origin.[25]

These results are suggestive of a gender norm. However, women married to East German men tend to earn a larger share of household income, and couples might simply be optimizing based on each member's potential earnings. To test for this, we re-weight the West German couples to have the same distribution of predicted female share of household income as the East German couples four years following a move.[26] This puts more weight on West German couples where the woman earns a higher share of household income. The results in Appendix Figure A-8 show similar patterns with this re-weighting, indicating that differences in women's income share between the groups do not account for the patterns in Figure 5.

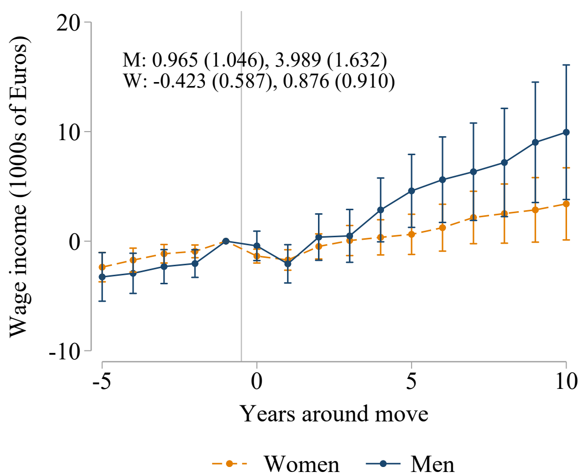
Along with being suggestive of a gender norm driving the results, the East/West German comparison also helps rule out explanations such as employers anticipating that women will not be willing to move and therefore do not make women job offers, or that women are generally more risk averse or less ambitious than men and so do not apply for jobs elsewhere. Explanations like these would require employers to know whether women have spouses from East or West Germany, or that personality traits like risk aversion vary by spouse's region of birth.

[25]Appendix Figure A-7 shows the results for other subsamples, such as when only the man is East German.

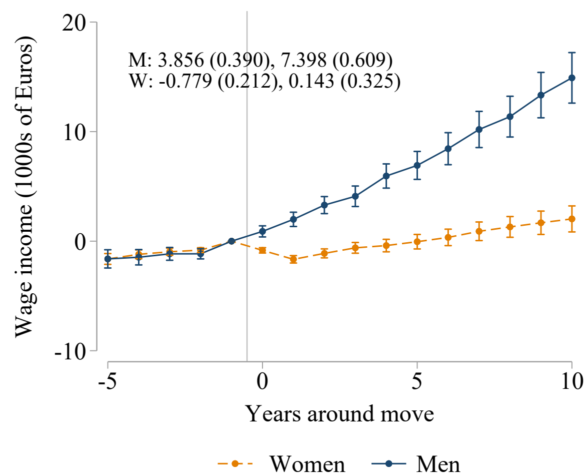
[26]Section 5.2.2 describes how we predict female share of household income.

Figure 5: East vs. West German Origin

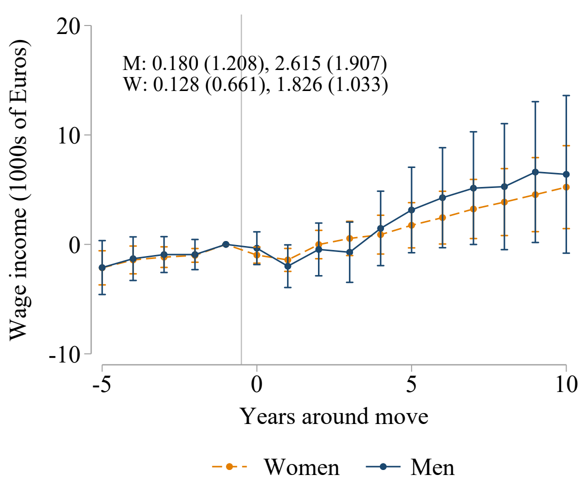
(a) At Least One Spouse of East German Origin



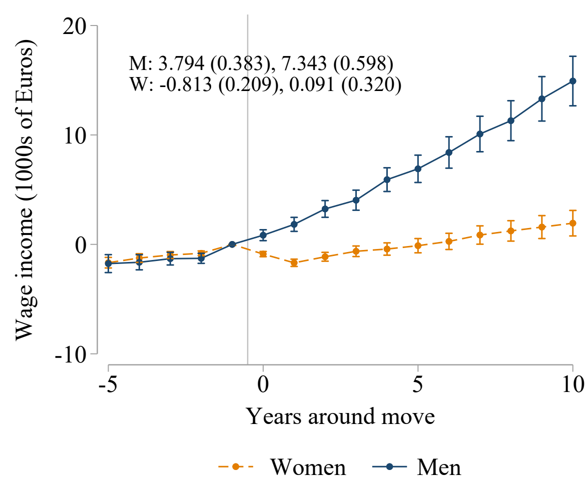
(b) No Spouse of East German Origin



(c) Male Spouse of East German Origin



(d) Male Spouse Not of East Germany Origin



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 German subsamples. These subsamples are defined by the place of the first employment of one of the spouses or the male. 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 left 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).

5.2 Model-Based Test

The fact that the gender gap in the earnings effects of relocation is substantially smaller for East German couples than West German couples suggests a role for a gender norm that prioritizes the man's career. To formally test this, we set up and estimate a model of the household migration to quantify the importance of this gender norm. We extend a standard model of collective decision-making in which couples maximize household income by allowing couples to potentially place more weight on income earned by the man relative to the woman (Foged 2016).[27] We use the model to derive empirical tests for whether the results in the previous sections can be rationalized within a standard collective model (i.e., gender-blind joint income maximization) by gender differences in potential earnings.

We begin by presenting theoretical results that directly motivate additional empirical analysis. We then present the additional empirical results, and we use these results as moments to estimate the model parameters separately for each country. We use the estimated model parameters to test (and reject) the gender-blind collective model in both countries, finding larger deviations in Germany than 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.

5.2.1 Model

Model setup. There is a unit mass of households, each with 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 gender-specific

[27] Foged (2016) also develops a model where households discount income earned by the wife relative to the husband. We build on and extend this model. While Foged (2016) focuses on deriving predictions about how the probability of moving varies with the female earnings share of household income (i.e., the determinants of moving), we focus on how the expected change in income after moving varies with the female earnings share (i.e., the effects of moving). We show in Appendix C.3 that the predictions in Foged (2016) on how the probability of moving varies with the female earnings share are somewhat sensitive to functional form assumptions and allowing for assortative mating.

log-normal income distribution: $\log(y_{i1}) \sim N(\mu_i, \sigma^2)$.[28] With this setup, the average gender earnings gap in period 1 is $E[y_{M1}] - E[y_{F1}] = \exp(\mu_M + \sigma^2/2) - \exp(\mu_F + \sigma^2/2)$, and we define $s = y_{F1}/(y_{M1}+y_{F1})$ to be the female's share of total household income in period 1.

Migration decision. For simplicity, we assume that each household member receives the same income in period 2 as 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, $y_{i2} = (1+\varepsilon_{i2})y_{i1}$, where $\varepsilon_{i2} \sim N(\mu_r, \sigma_r^2)$. The μ_r and σ_r parameters capture heterogeneity in the returns to migration, and we assume the distribution of potential returns is the same by gender when expressed as a percent of baseline income. We define a **collective household** as a household that 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 denote 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 $\Delta y_M + \Delta y_F > c$. We define a **non-collective household** as a household that places a different weight on the female's income compared to the male's income, using a relative weight parameter $\beta \neq 1$; this type of household will move if and only if $\Delta y_M + \beta\Delta y_F > c$ (if $\beta = 1$, then the household is a collective household based on the previous definition). If $0 < \beta < 1$, then the household places less weight on the female's income compared to the male's income. The first proposition describes the average change in income from moving (conditional on moving) in a population of collective households:

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 C.*

If there is a baseline gender gap in earnings favoring men, men will systematically benefit more from moving than women do in collective households. The returns to migration are identically distributed in proportional terms, and the same proportional gain translates into a larger income gain for the man if his permanent income is higher than his spouse's.

[28] 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 Appendix C.2 and show in simulations that our main propositions go through with these extensions.

Thus, the man is more likely to draw a potential income in period 2 that exceeds the household's cost of moving and, conditional on moving, it is more likely that the move benefits the man than the woman. This implies that the previous reduced-form empirical results on their own do not reject a standard collective model or necessarily point to an inefficiency in household decision-making.

While Proposition 1 shows that it is not possible to rule out a collective model based on the gender gap in average returns to moving, the next proposition shows that for collective households with $s = 0.5$, the expected return to moving is the same for men and women:

Proposition 2 *If 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 C.*

Proposition 2 implies that if two spouses have identical income in period 1 and the same distribution of potential returns to moving, then it is equally likely that each ends up being the "trailing spouse" when the household chooses to move. The man and woman are symmetric in this case, and so if $\beta = 1$, then there is no gender gap in the effect of moving on earnings.[29]

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 on income earned by the woman, so that $0 < \beta < 1$. This may reflect a social norm that prioritizes a man's career over a woman's, or that women on average care less about wages and career progression than men.[30] The next proposition shows that in non-collective households with $0 < \beta < 1$, the expected return to moving is larger for men than women at $s = 0.5$, with the gap decreasing as β approaches 1.

[29] Propositions 1 and 2 are both established in a simplified setting, with the baseline log income distributions for men and women having equal variance and no assortative mating. Appendix C presents proofs and simulations of extended versions of the baseline model that relax each of these assumptions.

[30] For example, Mas and Pallais (2017) find that women are more willing than men to take a pay cut in order to be able to work from home and to avoid irregular working hours. Similarly, women may agree to move for their partner's career, while other household decisions may be more important to them.

Proposition 3 *If 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 C.*

Propositions 2 and 3 provide a sharp empirical test of the collective household model: if we continue to find that men disproportionately benefit from moving compared to women within the set of households at $s = 0.5$ (or *a fortiori* among $s > 0.5$ households), then we will conclude that the households' behavior is not consistent with a collective model and that households put less weight on income earned by the woman. These theoretical results imply that we should examine the earnings effects of migration after "zooming in" on households near $s = 0.5$.

5.2.2 Estimating the Female Share of Household Income, $\hat{s}$

To operationalize the empirical tests suggested by the model, we need to construct a measure of (predicted) female share of household income. We use predicted earnings because actual earnings are subject to temporary earnings differences due to one spouse being unemployed or reducing work hours. To do so, we first estimate a Mincerian regression that we use to assign a predicted income to each person in our sample. Specifically, we run a Poisson regression, separately by country, on a sample of all individuals aged 25-54. The regression model relates annual earnings to a large set of controls: potential experience dummies, a child dummy, education dummies, and year dummies. In Sweden, we also include detailed college major indicators for individuals who attended college or vocational training, and we interact these college major indicators with the education dummies. For Germany, we use the 3-digit code of the first occupation instead of college major.[31]

[31] We use a Poisson model of earnings instead of an OLS model of log earnings to allow for observations with no earnings. Because the gender gap in non-employment is fairly small in both countries in our sample, we find very similar results using a log-linear OLS model instead (Appendix Figure A-9). More details on the predicted income methodology are shown in Appendix B.

We estimate the prediction model separately by gender. Using a gender-specific earnings model allows for the possibility that households expect the woman to earn less (conditional on occupation, education, etc.) due to factors such as gender discrimination in the labor market, or moving to part-time work following childbirth. Moves that favor men due to these factors will load onto the collective-model interpretation. Our test of gender norms is therefore a stringent test that, conditional on these broader gendered patterns in the labor market, couples down-weight the woman's earnings when deciding whether and where to move.

We use the regression models to construct a measure of predicted income four years post-move for each member of the couple, and we calculate the predicted female share of household income.[32] Appendix Figures A-10 and A-11 show the distribution of the resulting predicted incomes for the men and women in our sample, and the predicted female share of household income. We use the predicted female share of household income, $\hat{s}$, as our empirical proxy for s in the model.

5.2.3 Heterogeneity in the Earnings Effects of Relocation by $\hat{s}$

To assess how the earnings effects of moving vary with $\hat{s}$, we run our event study specification separately for three groups of households. Ideally, we would simply compare households in which women earn the majority of household income to those in which men earn the majority of household income. However, when women earn the majority of household income, they typically earn just over 50%, while when men earn the majority, they often earn much more than 50%. We therefore split the sample into couples where the woman earns (1) much less than 50%, (2) less than but close to 50%, or (3) more than 50%.[33]

[32] We use the predicted female share rather than the actual share in part because our layoff results indicate a gender-specific effect of layoffs on the probability of moving, so women with very high household income shares in the year before a move may be in households where the man was recently laid off. In these households, the fact that the man disproportionately benefits from moving could mechanically come from mean reversion. Similarly, a man and a woman may have similar current earnings but the man may be predicted to earn much more in the future.

[33] Appendix Tables A-3 and A-4 show summary statistics for these subsamples.

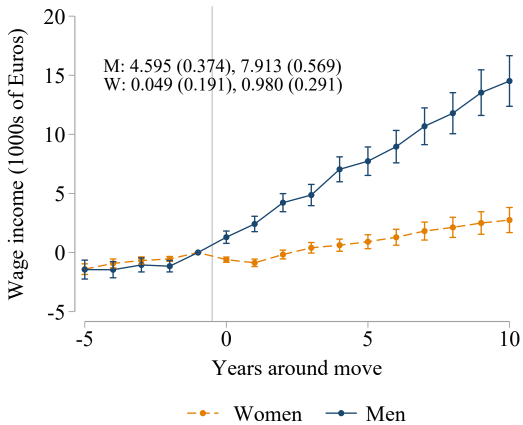
Specifically, the first group comprises households in which the woman is predicted to earn less than 39.0% in Germany and less than 40.0% of household income in Sweden (these households have average $\hat{s}$ of 27.5% and 33.4% in Germany and Sweden, respectively). The second group corresponds to households where women are predicted to earn between 39.0% and 50% of household income in Germany and between 40.0% and 50% in Sweden. This second group is defined so that the average $\hat{s}$ is equal to 1 minus the average $\hat{s}$ in the third group, which is households in which the woman is predicted to earn more than 50% of household income (the average $\hat{s}$ in this group is 56.3% in Germany and 55.8% in Sweden). Comparing the second and third groups of households allows us to test whether households act "symmetrically" when the woman earns share $\hat{s}$ of household income versus when the man earns that same share, for values of $\hat{s}$ "close" to 0.5.

The results are shown in Figure 6. First, the gender gap in the effect of moves is largest among the couples in which the woman's predicted household income share is smallest (panels (a) and (b)). This is consistent with the primary earner's job opportunities being influential in whether to move. Second, a comparison of the last two groups (in which the woman or the man, respectively, has a predicted earnings share of 43-44%) points to an asymmetry based on whether the man or the woman is the primary earner. For households with $\hat{s} < 0.5$, men benefit more from relocation than women in both countries (panels (c)and (d)). For households with $\hat{s} > 0.5$, women do not benefit more than men in Germany (panel (e)), while in Sweden they do (panel (f)). However, based on the six-year average, even in Sweden, women's advantage from moving when $\hat{s} > 0.5$ (€494) is smaller than men's advantage in the symmetric subsample with $\hat{s} < 0.5$ (€660) (see panel (d) versus (f)). If the earnings gap were simply due to households maximizing joint income ($\beta = 1$), then our model tells us we would see the "equal and opposite" gender earnings gap favoring women in households where the woman is predicted to earn more, compared to the "symmetric" households where the man is predicted to earn more. The results for Germany clearly reject this, while in Sweden we see an "opposite but not equal" pattern. This suggests that β is considerably less than 1 in Germany and less than but close to 1 in Sweden. We test this formally in section 5.2.4.[34]

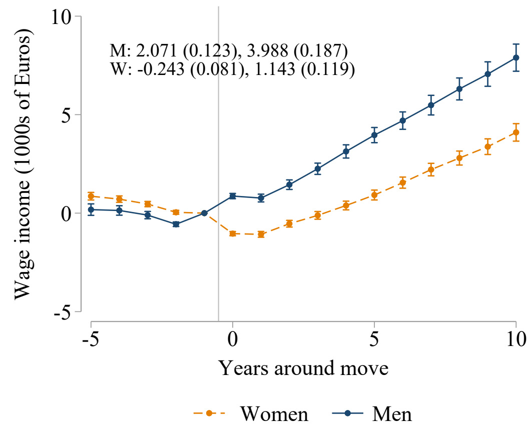
[34] In Appendix Figure A-12 we test whether moves lead to couple dissolution, particularly among couples in which the woman is the higher earner. The outcome is an indicator that a couple shares a family ID, indicating that they share an address, are married, or have a child. We see no significant change in couple dissolution both for the whole sample (panel a) and for the three income share groups (panel b).

Figure 6: Impact of Move on Wage Income by Predicted Female Share of HH Income

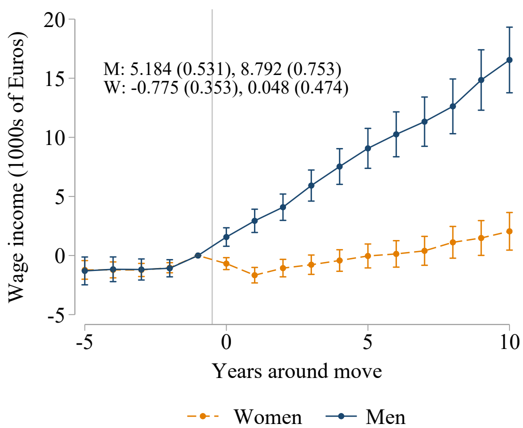
(a) $\hat{s} < 39\%$, Germany



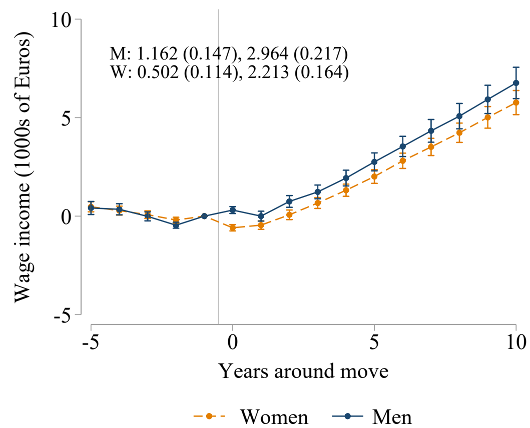
(b) $\hat{s} < 40\%$, Sweden



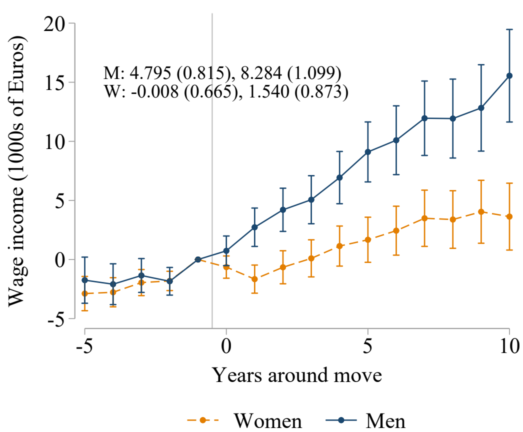
(c) $39\% \leq \hat{s} < 50\%$, Germany



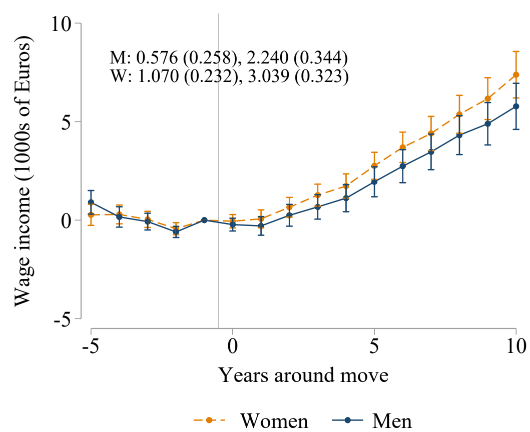
(d) $40\% \leq \hat{s} < 50\%$, Sweden



(e) $\hat{s} \geq 50\%$, Germany



(f) $\hat{s} \geq 50\%$, 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 left 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 running a Poisson regression of individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old.

In Appendix Figure A-13 we show the results using the *actual* female share of household income in the year prior to a move. Indeed, we see in panels (e) and (f) that many cases in which women earn the majority of household income seem to be due to men temporarily experiencing unemployment or a low wage, further justifying the use of predicted income share.

We summarize the results from the heterogeneity analysis in Table 3, which reports the effects of relocation on earnings for men and women. Each estimate represents the average 6-year effects of relocation on earnings by taking a simple average of the event study estimates from $t = 0$ to $t = 5$. The first row reports results for the full sample and the remaining rows report results for each subsample defined by $\hat{s}$. (The notation s^* denotes the minimum $\hat{s}$ to be in one of the "symmetric" groups around $\hat{s} = 0.5$.)

Table 3: Variation in the Effects of Moving by Predicted Female Share of Household Income

	Germany		Sweden	
Predicted Female Share of Household Income, $\hat{s}$	Men (1)	Women (2)	Men (3)	Women (4)
Full sample	4.468	-0.049	1.744	0.026
	(0.333)	(0.183)	(0.105)	(0.073)
$\hat{s} < s^*$	4.595	0.049	2.071	-0.243
	(0.374)	(0.191)	(0.123)	(0.081)
$s^* \leq \hat{s} < 0.50$	5.184	-0.775	1.162	0.502
	(0.531)	(0.353)	(0.147)	(0.114)
$\hat{s} \geq 0.50$	4.795	-0.008	0.576	1.070
	(0.815)	(0.665)	(0.258)	(0.232)

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 reported values correspond to the 6-year averages of the post-move point estimates, from $t = 0$ to $t = 5$. Note that $s^* = 0.39$ for Germany, and $s^* = 0.40$ for Sweden. s^* is chosen so that the conditional expectation of $\hat{s}$ in $\hat{s} \geq 0.5$ and $s^* \leq \hat{s} < 0.5$ is symmetrically distributed around 0.5.

Our main results are based on constructing $\hat{s}$ from gender-specific earnings prediction models. By using gender-specific predictions, we assume that average gender gaps in earnings conditional on education and experience come from labor market factors such as discrimination, lower labor demand in jobs that women prefer, unobserved gender-specific productivity, or even women's preferences (e.g., preferences for leisure). By assuming that the average gender gaps do not arise from a gender norm that prioritizes men's careers, we are constructing a conservative test of $\beta = 1$. This is because, if households discount income earned by the woman, women might respond by working less or choosing lower-paying jobs. Our gender-specific predictions classify those behavioral responses as lower potential earnings for women or gender-specific preferences when they could be indicative of a gender-biased household norm.

5.2.4 Model-Based Estimation

We now use the reduced-form six-year-average estimates in Table 3 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 estimates are reported in Table 4. Consistent with the summary statistics reported in Table 1, there is a larger baseline earnings gender gap in Germany than in Sweden (i.e., a large difference in mean log income).[35]

With the baseline income parameters estimated, there are four remaining model parameters to estimate: 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 relative weight the couple places on women's income (β).[36]

[35] We simulate both predicted income and actual income in order to allow for measurement error in $\hat{s}$, and we calibrate the degree of measurement error based on the R^2 of an OLS regression of actual income on the predicted income generated from the gender-specific Poisson model. We find R^2 values of 0.201 and 0.194 (Germany, men and women) and 0.319 and 0.300 (Sweden, men and women). Measurement error could bias estimates of β downward by attenuating differences across the subsamples defined by $\hat{s}$, but we show in our sensitivity analysis that this bias is very small in both countries (Appendix Table A-5).

[36] We assume that all households have the same mobility cost, but we can easily extend the 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 and use additional migration data (e.g., migration rates for different subsamples of households) as additional moments to estimate σ_c separately from the other parameters. Importantly, doing so would have little influence on the estimate of β. One way to see this is that we can choose different values of the migration rate and re-estimate the model, and there is no meaningful impact on β (while the returns to migration and mobility cost parameters are affected); see Appendix Table A-5 for details. Thus, we ignore heterogeneity in mobility costs for simplicity, as β is our primary parameter of interest.

Table 4: Model Parameters

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Log normal scale parameter, men μ_M	3.49	3.17
Log normal variance parameter, men σ_M	0.71	0.65
Log normal scale parameter, women μ_W	2.71	2.49
Log normal variance parameter, women σ_W	0.88	0.75
Panel B: Model Parameter Estimates		
Mean returns to migration, μ_r	-0.145	-0.034
	(0.081)	(0.033)
Standard deviation in the returns to migration, σ_r	0.127	0.049
	(0.049)	(0.024)
Household mobility cost, c	2.113	1.775
	(0.893)	(0.479)
Relative weight on woman's income compared to man's income, β	0.481	0.795
	(0.144)	(0.095)

Notes: Panel A displays the parameters used for the baseline log-normal income distributions for men and women. Column (1) displays parameters for Germany, while Column (2) displays parameters for Sweden. 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 $s^* \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 3. Note that $s^* = 0.39$ for Germany, and $s^* = 0.40$ for Sweden. Notes in Table 3 explain how s^* is chosen.

To identify and estimate the four parameters, we use as moments four of the estimates in Table 3: the average change in income from relocation for men and women in two of the subsamples that group households based on $\hat{s}$, focusing on the two subsamples with values of $\hat{s}$ closest to = 0.5 (our "symmetric split" subsamples). The fifth moment that we use is the average migration rate, which we calculate from a random sample that is matched to the age distribution of our sample of movers; we estimate a 10-year migration rate of 4.08 percent in Sweden and 3.69 percent in Germany. Intuitively, identification works as follows: if $\beta = 1$, then the average change in income for men and women at $\hat{s} = 0.5$ should be "equal and opposite" according to Proposition 2. This tells us that the extent to which women do not benefit more than men in the $\hat{s} \geq 0.5$ subsample primarily identifies the parameter β, and we can estimate β by comparing the results for the $\hat{s} \geq 0.5$ subsample to the $s^* < \hat{s} \leq 0.5$ subsample. The identification of the other three parameters follows straightforwardly from the fact that the migration model has the structure of a standard Roy model. The μ_r, σ_r and c parameters are jointly identified from the average earnings return for men and women along with the migration rate. Holding constant the other two parameters, higher average earnings for men and women conditional on moving means a higher value of μ_r, σ_r, or c. Similarly, holding the other parameters fixed, a higher migration rate implies a lower value of c, a higher value of μ_r, and either a larger or smaller value of σ_r, depending on whether c as a share of pre-move income is larger or smaller than μ_r.[37]

[37] In a version of the model with a single individual making a migration decision, μ_r, σ_r, and c would not be separately identified from the average earnings return and migration rate. But we can identify the three parameters when both spouses are drawing independently from the same potential returns to migration distribution because having average earnings separately for men and women provides a third moment. Additionally, since we use five moments and have only four unknown parameters, we can relax our baseline model to allow for the earnings return to migration to be correlated. We find similar results in this extended model, which is likely because we estimate a very small correlation across spouses in the returns to moving (see Appendix Table A-5).

To estimate the model parameters, we use a simulated method of moments approach, which entails simulating the model a large number of times and searching for the combination of model parameters that minimizes 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 the estimated moment. The Appendix provides more details on the estimation procedure, calculation of standard errors, and over-identification tests we can conduct since we have more moments than parameters.[38,39]

The main parameter estimates and standard errors are reported in Table 4.[40] The estimated distribution of the returns to migration shows slightly greater dispersion in Germany than in Sweden. We find larger estimated mobility costs in Germany, although the baseline income is also larger so as a percentage of baseline income, the mobility costs are fairly similar between the two countries. The estimated household mobility costs are large in both countries, which rationalizes the large average returns to moving alongside fairly low migration rates.[41]

[38]While our main results are based on a standard simulated method of moments approach, we recover very similar estimates from an alternative two-step iterative estimation approach (see Appendix Table A-5). For this alternative, we first estimate the three model parameters other than β (i.e., μ_r, σ_r, and c) using three moments, the average earnings return for men and women in the $s^* \leq \hat{s} < 0.5$ subsample and the migration rate. In the second step, we fix those three parameters at the estimated values and use the average earnings return for men and women in the $\hat{s} \geq 0.5$ subsample as two moments to estimate β. We then iterate, using the β from the second step and re-estimating the other three parameters with the three moments from the first step. We continue this algorithm until the parameter estimates converge. This iterative approach shows another way to think about the identification of the model parameters. We identify the Roy model parameters (σ_r, μ_r, c) using average earnings returns for men and women and the average migration rate, and then, given these parameters, we identify β by comparing the returns to moving in the $\hat{s} \geq 0.5$ subsample versus the full sample.

[39]In the Appendix we report results that assume that $\hat{s}$ is measured without error, and we find very similar results. The reason is that while measurement error around $\hat{s} = 0.5$ biases β away from 1, there is also measurement error around $\hat{s} = s^*$ (the lower bound to be in one of the two subsamples used in the estimation), and this biases β towards 1. Our results suggest that these biases roughly cancel out.

[40]The standard errors are calculated using the following variance-covariance matrix: $V = (\hat{G}'(\hat{W})^{-1}\hat{G})^{-1}$. The matrix $(\hat{W})^{-1}$ is a diagonal matrix using the inverse of the estimated sampling variances for each of the reduced-form moments, and $\hat{G}$ is the gradient of each simulated moment with respect to each model parameter, which we calculate numerically.

[41]Since the model is a two-period model, we can interpret the magnitude of the household mobility cost parameter as an approximate annualized cost, which is estimated to be €2,113 in Germany and €1,775 in Sweden. For young households considering a 30-year return to migration, the migration cost would be 30 times the annual flow cost, ignoring discounting, or roughly €63,000 in Germany and €53,000 in Sweden. These estimated costs would be even larger if we allowed for non-financial reasons for migration. By comparison, Kennan and Walker (2011) estimate average mobility costs of about 312,000 US dollars.

Our main parameter of interest is β, which is estimated to be $\beta = 0.795$ (standard error $= 0.095$) in Sweden and $\beta = 0.481$ (standard error $= 0.144$) in Germany.[42] We can reject that $\beta = 1$ in both countries at conventional levels of statistical significance.

Table 5, Panel A, shows the simulated empirical moments at the estimated model parameters, and reports an extremely good model fit. One way to assess the economic significance of $\beta < 1$ is to simulate the model with $\beta = 1$. Panel B of Table 5 shows that imposing $\beta = 1$ while holding the other parameters constant results in a worse model fit, as expected; the restricted model is rejected at the 1 percent level in both countries.[43] To quantify how much norms contribute to the post-move gender gap, we calculate how much the gap narrows when we impose $\beta = 1$. For the full sample, the gap would be 32% smaller in Germany and 26% smaller in Sweden if couples put equal weight on men's and women's earnings. We also repeat the exercise for the "symmetric split" subsample – the couples where men and women have comparable potential earnings – whom we used to estimate the model. Here norms explain a considerably larger portion of the gap: the gender gap in the effect of moves would be 62% smaller in Germany and 82% smaller in Sweden if β were equal to 1.[44]

Table 5 also reports the simulated earnings effects of relocation for men and women in the untargeted $\hat{s} < s^*$ subsamples. The main reasons we do not directly target these moments in the estimation are that we are already over-identified (5 moments and 4 parameters), and we do not want to impose the same β for the households with the most gender-unequal predicted earnings; one might expect β to be lower for them than for the "symmetric split" of households around $\hat{s} = 0.5$ that we use to estimate β. The simulated model, using our parameter estimates, reproduces the large gender gaps in the $\hat{s} < s^*$ subsample, though this is also true when we impose $\beta = 1$.

[42] As mentioned earlier, roughly 13% of married couples in Germany do not share a last name. Assuming that these couples have $\beta = 1$ gives us an upper bound of $\hat{\beta}$ in Germany of $0.87 \times 0.49 + 0.13 \times 1 = 0.56$.

[43] Appendix Table A-6 reports the model fit when we impose $\beta = 1$ and re-estimate the other model parameters, and the estimated model parameters from this restricted model are reported in Table A-7. This model also has a worse fit than the results in Table 5 (Panel A), particularly for Germany. The over-identification test rejects at the 1 percent level in Germany and 10 percent level in Sweden.

[44] Interestingly, we find norms explain more of the gap in Sweden despite β being lower in Germany. This arises primarily because of the larger baseline gender wage gap in Germany; the ability of $\beta < 1$ to explain post-move gender gaps is larger if there is a larger gender wage gap at baseline.

Table 5: 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: Simulated Moments from Baseline Model				
Targeted Moments:				
$\hat{s} \geq 50$	4.636	0.069	0.672	1.139
$s^* \leq \hat{s} < 0.50$	5.166	-0.781	1.129	0.485
Household migration rate	0.037		0.041	
χ^2 [p-value]	0.005 [0.945]		0.300 [0.584]	
Untargeted Moment: $\hat{s} < s^*$	5.778	-1.163	1.567	0.118
Panel B: Simulated Moments Setting $\beta = 1$ *(holding other parameters constant)*				
Targeted Moments:				
$\hat{s} \geq 50$	2.851	2.542	0.515	1.326
$s^* \leq \hat{s} < 0.50$	3.947	1.222	0.986	0.673
Household migration rate	0.034		0.044	
χ^2 [p-value]	57.993 [<0.001]		12.386 [<0.001]	
Untargeted Moment: $\hat{s} < s^*$	5.364	0.013	1.474	0.251

Notes: This table presents the empirical estimates of the effects of moving by different gender-specific predicted female share of household income. These are compared to the baseline model estimates and alternative model estimates setting $\beta = 1$ and holding other parameters constant. χ^2 is a goodness-of-fit statistic. Note that $s^* = 0.39$ for Germany, and $s^* = 0.40$ for Sweden. Notes in Table 3 explain how s^* is chosen.

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

The larger departure from the gender-blind collective model in Germany is interesting because Germany also has a larger baseline gender gap in earnings (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: to simulate the effects of job layoffs on migration and the effects of childbirth on earnings.

5.3 Additional Implications of $\beta < 1$: Gender Differences in the Effect of Job Layoffs on Relocation and in "Child Penalties"

Another way to assess the explanatory power of the model and the $\beta < 1$ parameter estimate is to simulate the exogenous decline in income from a layoff, and then predict the change in the probability of moving depending on whether the male or female was laid off. We can then compare these simulated results to our reduced-form estimates of the effects of job separations caused by mass layoff events. Because those estimates were not targeted in the model estimation, we view this as a useful "out-of-sample" test of model fit.

We simulate the model at the parameters estimated in each country (reported in Table 4), 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. We calibrate the average earnings loss of job displacement to be 20.3% for men and 19.2% for women in Germany and 17.1% for men and women in Sweden based on the estimates reported in Illing et al.

(2023) and Bertheau et al. (2023). In both countries, we assume that 75 percent of this earnings loss is a loss of firm- or person-specific human capital that occurs regardless of whether the person relocates, but the remaining 25 percent of the earnings loss will be experienced if the worker remains in their current CZ but not if they relocate.[45]

The results are reported in Panel A of Table 6 and show that the model predicts a large gender gap in the effect of a job layoff on moving. The model can reproduce most of the actual gender gap in Germany (the male effect is 4.5 times as large as the female effect in the data and 3.8 times as large in the model prediction), but under-predicts the gender gap in Sweden. When we impose $\beta = 1$, we are not able to reproduce the empirical estimates as well. This exercise has clear limitations. For example, we have to make strong assumptions about the loss of specific human capital. To the extent this varies across countries or by gender, this will lead our model to diverge from the actual reduced-form results. The fact that our model does a fairly good job reproducing the mass-layoff results suggests that these other factors might be less important than accounting for the non-collective nature of household decision-making.

As an additional application of the $\beta < 1$ estimates, we simulate the change in earnings following the birth of a couple's first child to see how much the estimated $\beta < 1$ parameters can account for the so-called female "child penalty." To do this, we first estimate the child penalty for Germany and Sweden following Kleven et al. (2019b), and we report these results for our full samples in each country as well as for each of the $\hat{s}$ sub-samples formed as in our analysis of movers (i.e., the $\hat{s} < s^*$, $s^* \leq \hat{s} < 0.5$, and $0.5 \leq \hat{s}$ sub-samples). We report these empirical estimates in Panel B of Table 6, and we report all of the child penalty event study results graphically in the Appendix (Figures A-14 and A-15). Our child penalty estimates for the full samples in both countries closely match the results in Kleven et al. (2019b), and the new empirical result here is that the female "child penalty" is modestly smaller in the higher $\hat{s}$ sub-samples in both countries.[46]

[45]According to the estimates in Bertheau et al. (2023), about half of the earnings consequences of job displacement comes from losses of firm-specific pay premia, and the estimates of Card et al. (2023) indicate that about half of the variation in earnings across CZs is attributable to place effects. We thus assume that 25 percent of the earnings consequences of job displacement can be avoided through cross-CZ migration.

[46]The Kleven et al. (2019b) paper focuses on the female "child penalty" estimate ten years after the birth of the first child. We instead focus on the average effect on earnings over the first ten years, just as we do in our event study analysis of the earnings effects of relocation. Since we (and Kleven et al. (2019b)) estimate much larger female child penalty effects in the short run, this averaging leads to more negative female child penalty estimates in both countries, especially in Sweden.

Table 6: Model-Based Simulation

	Germany		Sweden	
	Men (1)	Women (2)	Men (3)	Women (4)
Panel A: Percent Change in Probability of Moving After Layoff				
Empirical estimates	58%	13%	96%	1%
Model-based simulations	79%	21%	76%	54%
Restricted model simulations ($\beta = 1$)	71%	39%	72%	65%
Panel B: Proportional Change in Earnings After Birth of First Child				
Empirical estimates				
Full sample	0.047	-0.762	0.023	-0.424
$\hat{s} < s^*$	0.057	-0.783	0.012	-0.446
$s^* \leq \hat{s} < 0.5$	0.048	-0.750	0.002	-0.391
$s^* \geq 0.5$	0.055	-0.719	0.031	-0.322
Model-based simulations				
Full sample	-0.029	-0.693	-0.069	-0.340
$\hat{s} < s^*$	-0.027	-0.776	-0.065	-0.383
$s^* \leq \hat{s} < 0.5$	-0.032	-0.605	-0.071	-0.321
$s^* \geq 0.5$	-0.035	-0.494	-0.087	-0.216
Restricted model simulations ($\beta = 1$)				
Full sample	-0.063	-0.135	-0.090	-0.199
$\hat{s} < s^*$	-0.060	-0.152	-0.085	-0.225
$s^* \leq \hat{s} < 0.5$	-0.066	-0.117	-0.093	-0.187
$s^* \geq 0.5$	-0.071	-0.095	-0.109	-0.124

Notes: Panel A reports empirical estimates and model-based simulations of changes in the probability of moving after an exogenous job displacement. The empirical estimates are calculated using the point estimates and mean from Table 2 columns (3) and (6). Panel B reports empirical estimates of the child penalty following Kleven et al. (2019a) and model-based simulations of the child penalty for both the full unrestricted model and a restricted model (imposing $\beta = 1$).

We then simulate a model of the child penalty by extending the model in Andresen and Nix (2022) to allow households to put less weight on income earned by the woman (as compared to the man), and to isolate the role of $\beta < 1$ we assume that the men and women in our sample of couples have identical ability in child-rearing and preferences for reducing labor supply following the birth of the couple's first child. We provide the full details of the child penalty simulations in the Appendix (see Section C.5), and we report the simulation results in of Panel B of Table 6. We find that we can quantitatively account for a large share of the estimated female child penalty in both countries in the full sample and every $\hat{s}$ sub-sample. One way to see the importance of $\beta < 1$ in quantitatively accounting for the female child penalty estimates in both countries is to compare the $\beta < 1$ simulation results to the bottom of Panel B of Table 6 which reports simulation results from a restricted model that imposes $\beta = 1$. While the restricted model results qualitatively match the empirical pattern that the child penalty is decreasing in $\hat{s}$ (coming from the fact that the female-male wage gap is increasing in $\hat{s}$ in the simulations), the magnitude of the female child penalty is always much smaller in the restricted model compared to the (unrestricted) model-based simulations and the empirical estimates.

The model simulation results also show that we do not *fully* account for the child penalty in both countries, which is consistent with the other factors that we assume away in the exercise also playing an important role (such as gender differences in comparative advantage in or preferences for child-rearing).

Taken together, we interpret the simulation results as providing useful "out-of-sample tests" of our model. Intuitively, our results suggest that the earnings effects of relocation, the effects of layoffs on the probability of moving, and the so-called female child penalty are all connected in both countries through our estimated β parameter, which captures the extent to which the couples in our sample choose to prioritize the man's career.

6 Alternative Explanations

This paper distinguishes between two main explanations for the gender earnings gap that emerges following a move: men's higher average earnings potential versus a gender norm. 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 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.

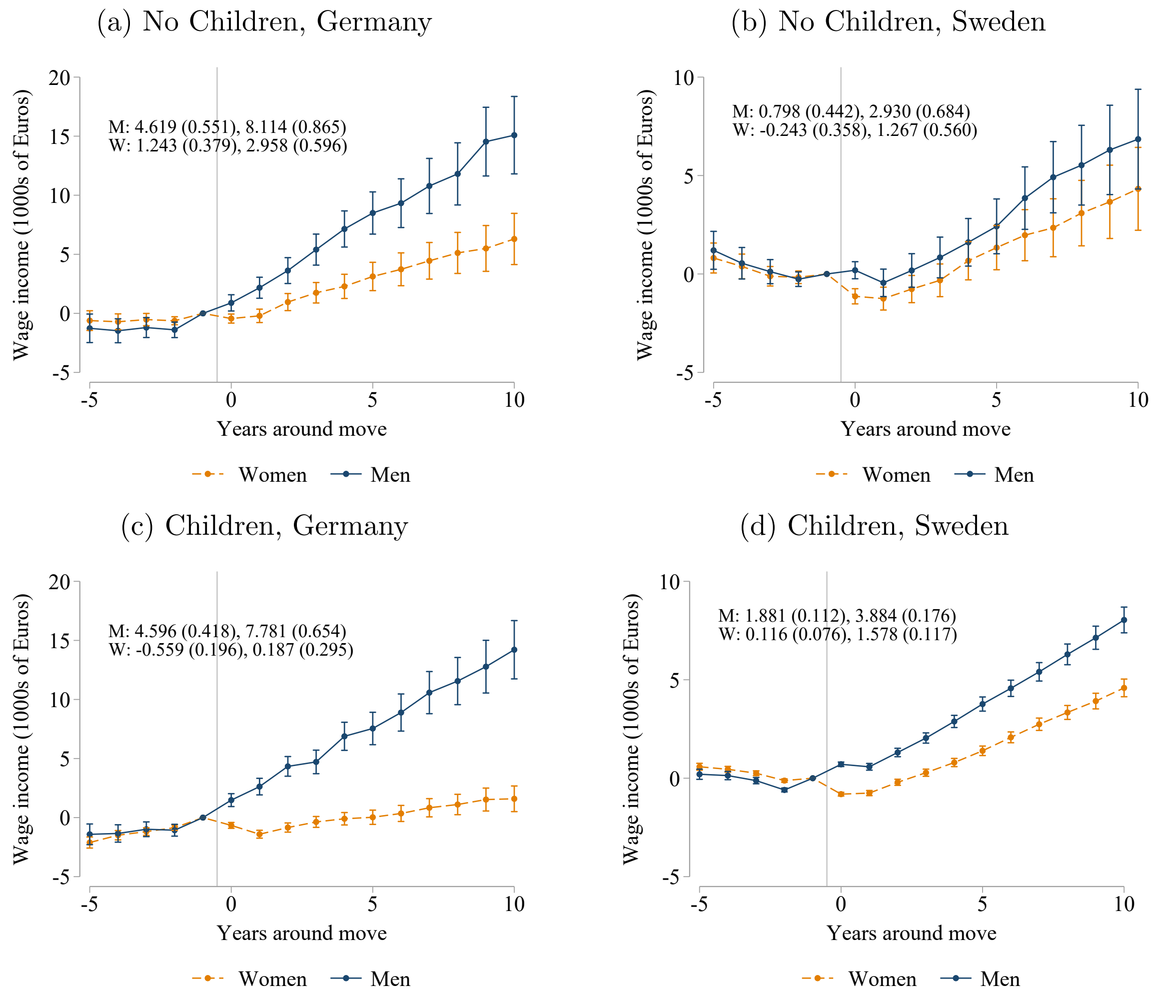
Anticipating the "Mommy Track" To group couples by whether the man or woman is the primary earner, we predicted men's and women's earnings four years after a move based on their observable characteristics. It is possible that, for couples that move, many women are anticipating having children which would lead them to leave the labor market or reduce their work hours. These women might therefore know that their earnings will soon be lower. Our prediction model incorporates this possibility in a population-average way, by predicting earnings based on gender and age, but if the phenomenon is more common among movers post-move, then couples' expectations about the female share of earnings will be lower than what we assign to them from our prediction model.

We test this explanation restricting our event-study analysis to couples that do not have a child. Figure 7 shows the event study results for couples that do not have a child, and for those that do. The earnings gap between men and women is only slightly larger for couples with a child than for couples without (by €1800 in Germany and €700 in Sweden, averaged over $t = 0$ to 5). It is therefore unlikely that the anticipation of the "motherhood penalty" is driving the full result.[47]

Gender Differences in Occupations It is possible that women are systematically in occupations with lower returns to moving. To test whether this can account for our findings, we estimate our event study equation but re-weight the sample so that women have the same occupation distribution as men. 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

[47] In addition, the motherhood penalty may in itself be the result of a gender norm, as argued in Kleven (2023) and in Appendix Section C.5.

Figure 7: Wage Income Results by Children



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 ($t-1$) for different subsamples by country. Children means becoming a parent before 2018 (Sweden) or 2022 (Germany), no children the opposite. 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 left 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).

have at least one man and one woman. (We lose about 30% of the layoff sample due to these restrictions.) We then re-weight the sample so that the women in the sample have the same occupation distribution as men. Because we do not have occupation information in Sweden, we instead re-weight by education×industry.

We estimate our event study equation for the three groups defined based on women's predicted share of household income. The results are presented in Appendix Figures A-16 (Germany) and A-17 (Sweden). In each figure we also show the unweighted results for comparison. Re-weighting by occupation changes the results very little in both countries.[48]

It is also possible that the occupations that men and women select into have different geographic concentrations. This would create an issue for our interpretation of the layoff results if, for example, women are able to easily get a new job in the same CZ whereas men must relocate to get a new job following a layoff. We therefore also estimate the effect of layoffs on moving with a re-weighted sample, such that women have the same occupation distribution as men. In Sweden, we again use education×industry as a proxy for occupation. Appendix Table A-8 presents the results. Although the likelihood that a couple moves when a man is laid off is still roughly twice as high as when a woman is laid off in both countries, the difference is no longer statistically significant in Germany and is only marginally significant in Sweden.

Non-Wage Amenities It is possible that women's returns to moving come in the form of non-wage amenities. For example, prior 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, following a move, women benefit from a shorter commute whereas men benefit from a higher salary.

[48] In Appendix Figure A-16 we re-weight using 4-digit occupation codes. Because we lose some sample due to there being too few women in certain occupations, we also re-weight by 3-digit codes in Appendix Figure A-18. The trade-off is that men and women are less comparable when using 3-digit codes than 4-digit codes.

We are able to test for two possible non-wage amenities using the Swedish data. First, because we can locate couples' homes and workplaces, we can calculate the distance to work and see whether it changes following a move. Panel (a) of Appendix Figure A-19 shows that, while men's average commute increases slightly, women's average distance from work does not change.[49]

Second, couples could be moving to be closer to grandparents, potentially to help with child-rearing. This explanation would be in line with Anstreicher et al. (2024), who find that American women tend to move back to their home locations in anticipation of childbirth. We first note that 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. In the Swedish data, we can link family members over generations. Appendix Figure A-19 shows no evidence that couples systematically move closer to a grandparent.

7 Conclusion

Over the past half century, there has been substantial gender convergence in the labor market, yet large gaps between men and women remain. These remaining gaps are in part attributable to the continuation of gendered roles within the household. This paper explores whether household decisions surrounding work tend to benefit men because of differences in earnings or because of a gender norm. We focus primarily on moves, establishing first that moves tend to benefit men's careers over women's. These results echo results in previous studies, but the unusually large and representative sample of couples in our analysis and graphical event-study analysis provides new evidence of this gender divergence. Men benefit almost exclusively through higher wages while women's losses are in part due to temporarily exiting the labor market or being employed for fewer days in the year.

[49] 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.

Our rich administrative data then allow us to quantify whether the earnings gap that emerges following a move is attributable to earnings differences or gender norms. Using a model of household decision-making in which households "discount" the income earned by the woman compared to the man, we test and reject a gender-blind collective model in both countries, with larger departures in Germany than Sweden. Overall, we conclude that a gender norm that prioritizes men's career advancement can simultaneously (and parsimoniously) account for gender gaps in both the earnings effects of relocation and the probability of moving following a job layoff, plus potentially other gender gaps such as 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.

Given the low moving rate in both countries, it is unlikely that gendered moves contribute significantly to the gender pay gap. The point of this paper is rather to quantify the degree to which moves favoring men are attributable to gender norms. Long-distance moves offer a useful laboratory to study gender norms in household decision-making because location is (typically) not a decision that each partner makes separately, optimizing for his or her career; it is a joint choice that requires trading off one person's career for the other's. We estimate a model using moves and then are able to use it to explore other household decisions that lead to gender inequality, such as work decisions following childbirth. Overall, our paper points to an important role for norms in explaining within-household earnings inequality.

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 simple and transparent as possible, but it should 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 easily be implemented in other countries. If the female “child penalty” is due in part to couples putting less weight on women’s earnings, then one should estimate lower β’s in countries with larger child penalties. Lastly, we conjecture that our model may be consistent with certain household bargaining models with limited commitment (e.g., Mazzocco (2007); Voena (2015)), and it would be useful to try to make this connection more precise. Such a connection may help think through the normative implications of $\beta < 1$ households choosing to “leave money on the table” when they pass up moves that would increase women’s earnings. For the questions that we have addressed in this paper, we did not need a specific micro-foundation of where the $\beta < 1$ parameter comes from, but for other questions it may be useful to give more details of exactly how and why households come to treat women’s income as less valuable than men’s.

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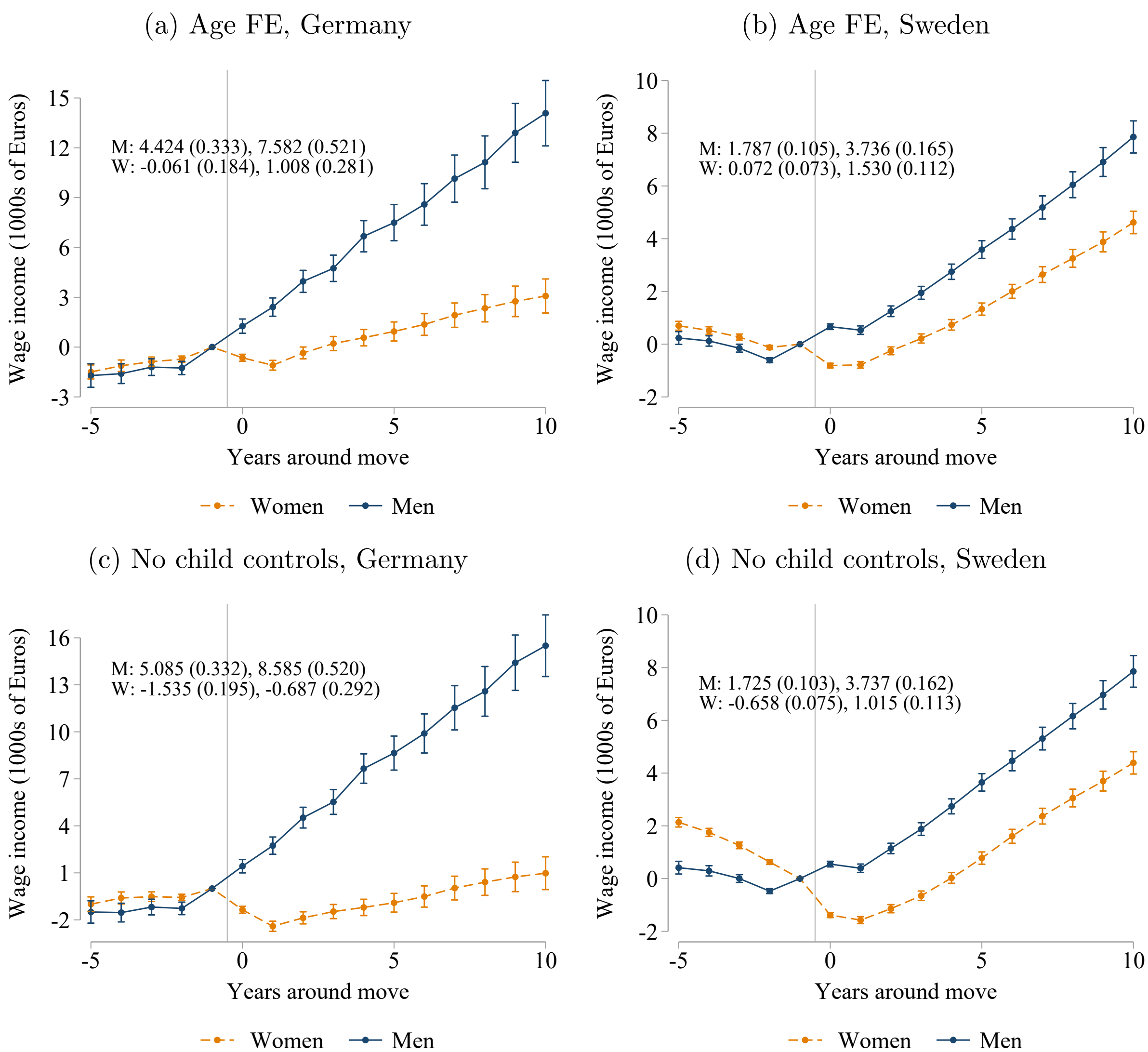
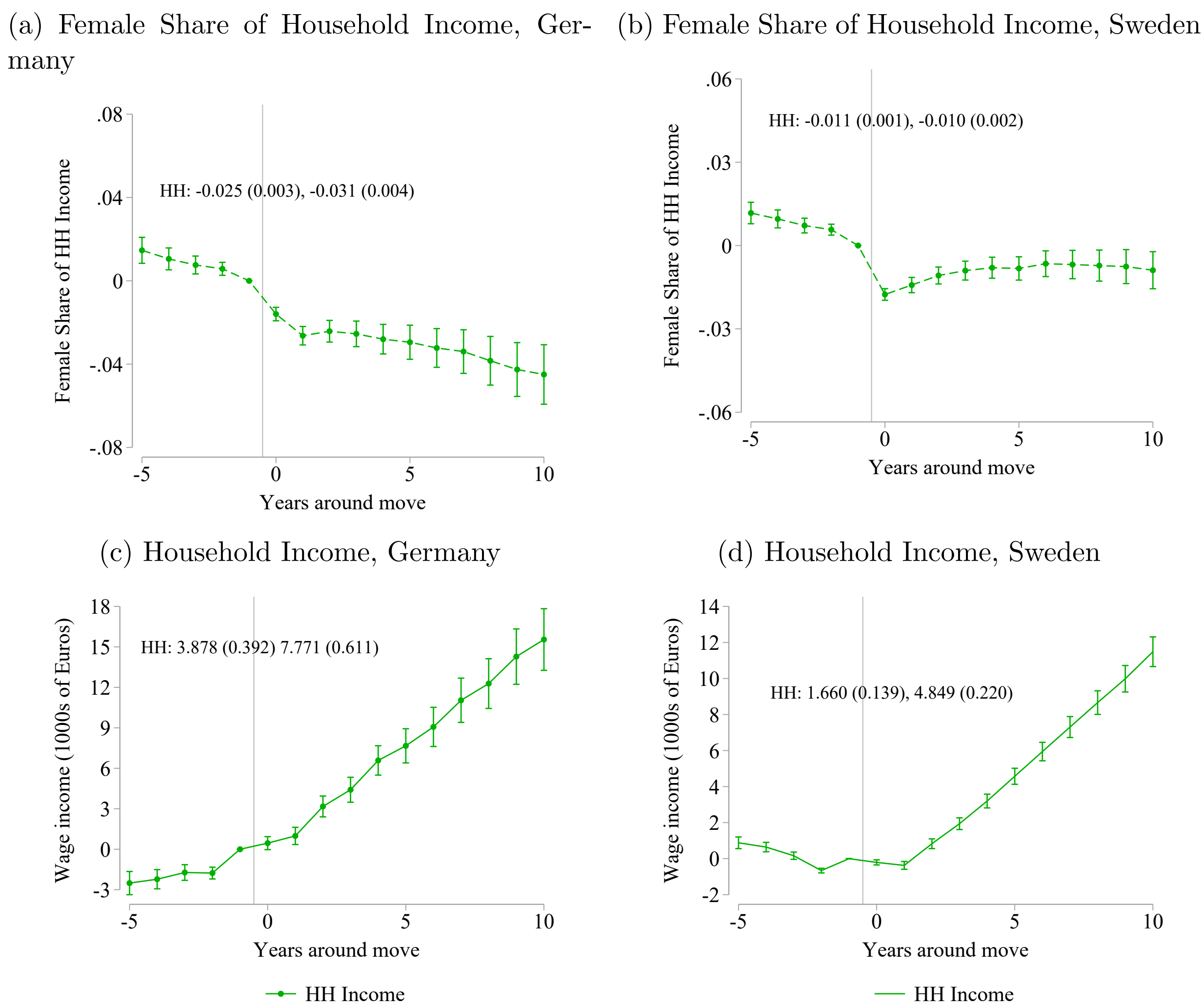
A Appendix: Additional Figures and Tables

Figure A-1: Impact of Move on Labor Earnings - Alternative Event Study Specifications



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 ($t-1$) using alternative event study specifications. Panel (a) and (b) show results for a specification with age fixed effects instead of age and age^2 and panel (c) and (d) show results for a specification excluding child event time dummies and the no child dummy. 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 left 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).

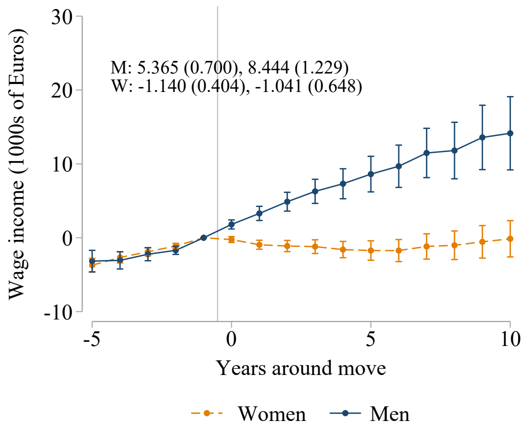
Figure A-2: Impact of Move on Household Outcomes



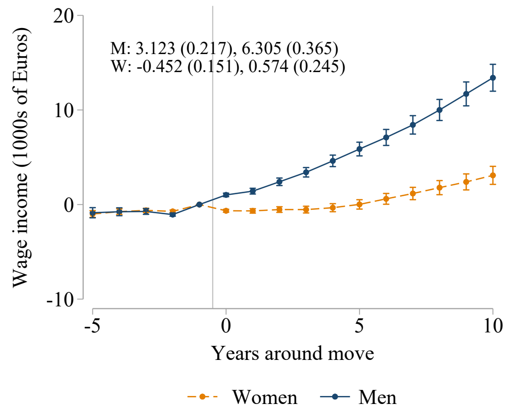
Notes: This figure displays the event study results that estimate the effect of moving on the female share of household income (panel a and b) and the household income (panel c and d) in each year relative to the year before the move (t-1). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the household level. The regressions are run at the household level, such that control variables are used from men and women. The coefficients and standard errors (in parentheses) in the upper left 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) for the household.

Figure A-3: Impact of Move on Wage Income – By Age Groups

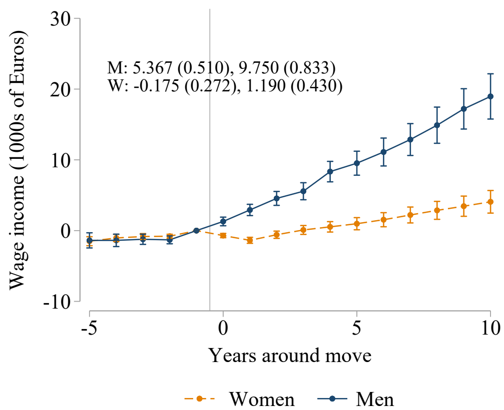
(a) 20-29, Germany



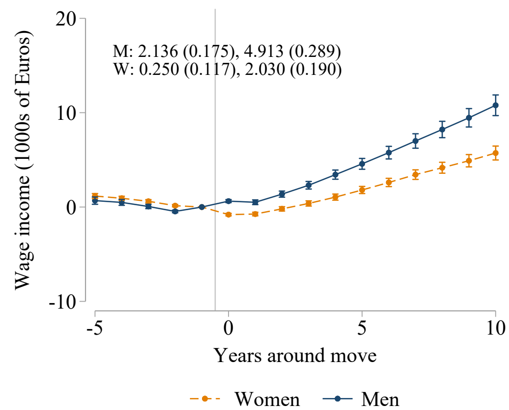
(b) Age 20-29, Sweden



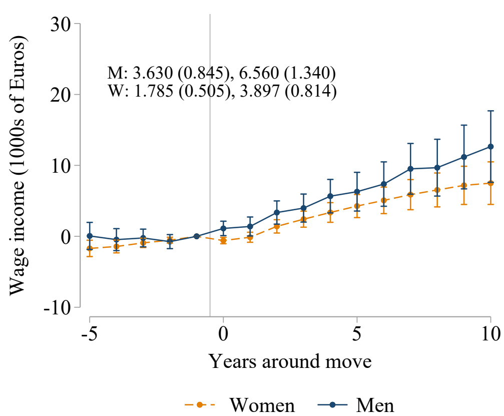
(c) Age 30-39, Germany



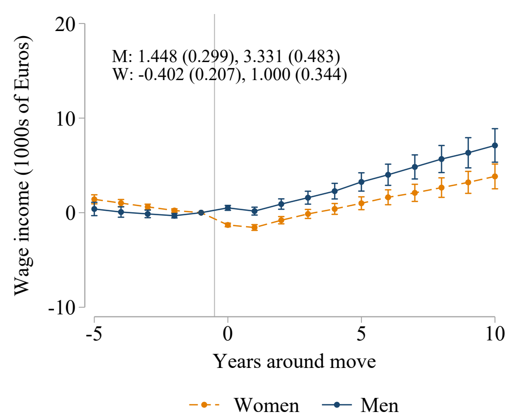
(d) Age 30-39, Sweden



(e) Age 40-50, Germany



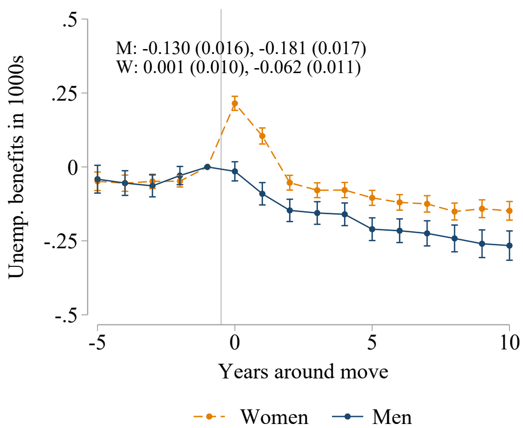
(f) Age 40-50, Sweden



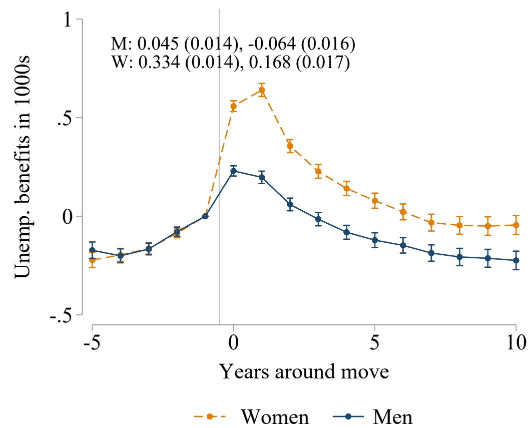
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t - 1$) for different age groups. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper left 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 A-4: Event Study Results on Other Measures of Employment

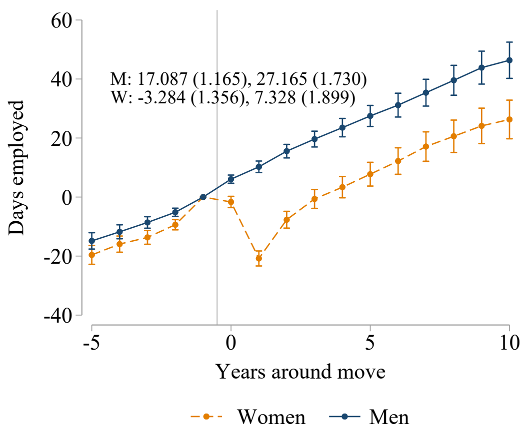
(a) Unemployment Benefits, Germany



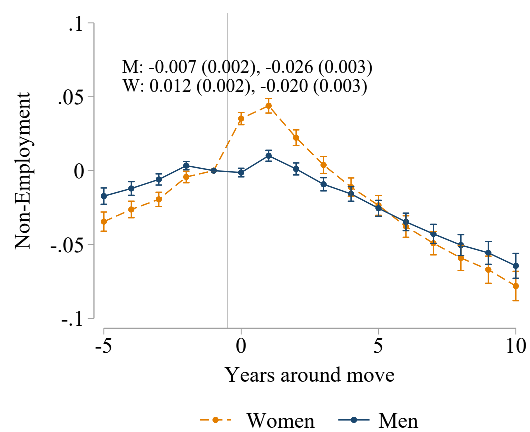
(b) Unemployment Benefits, Sweden



(c) Days Employed, Germany

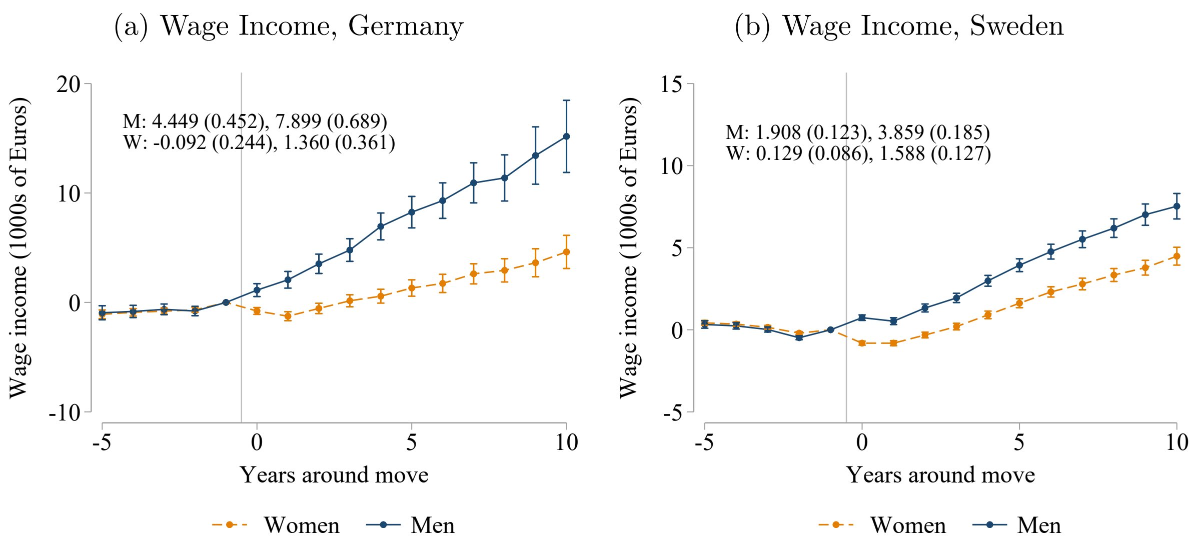


(d) Wage income < 2*price base amounts, Sweden



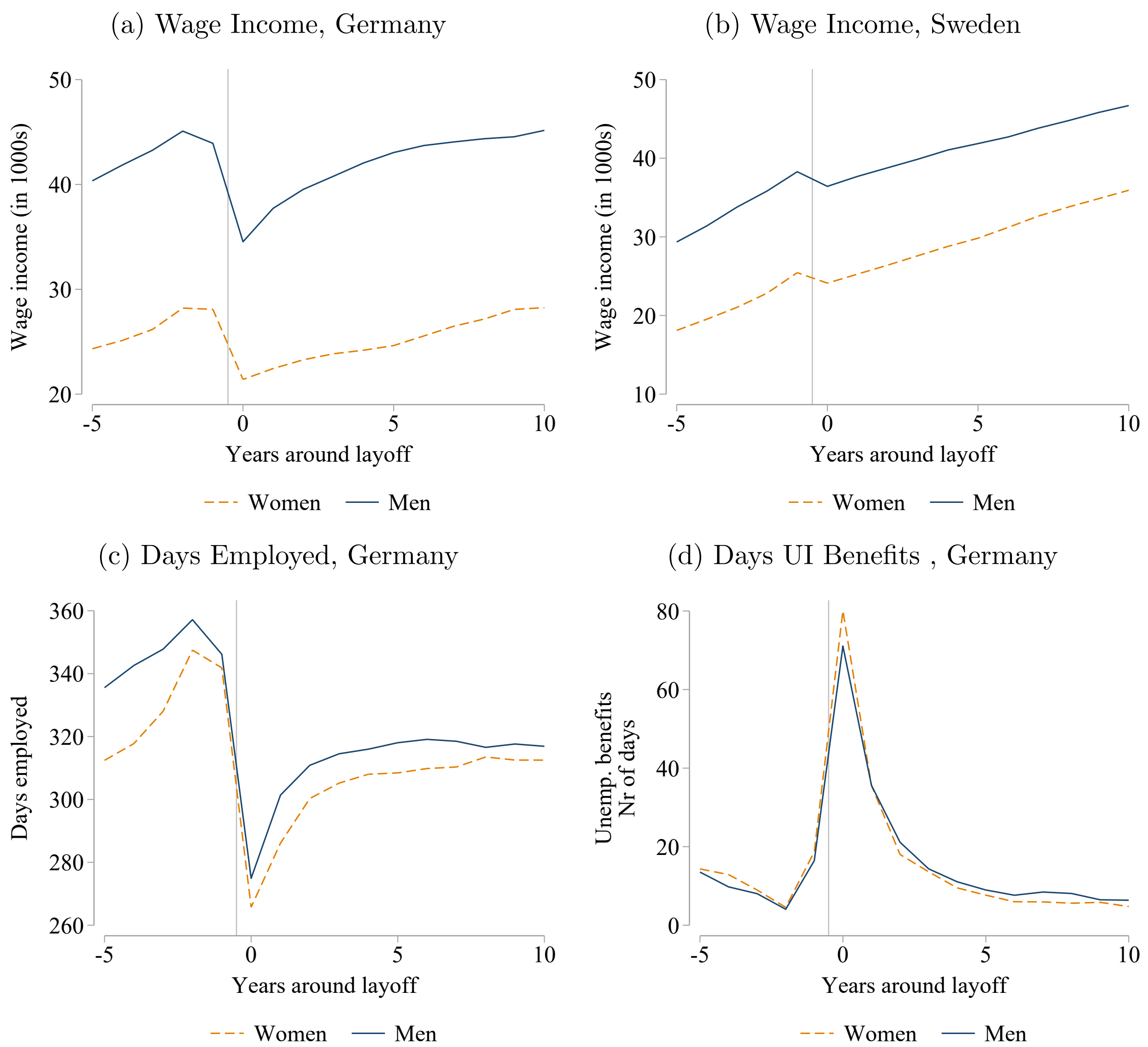
Notes: This figure displays the event study results that estimate the effect of moving on different outcomes in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper left 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). Unemployment benefits are measured in 2017 Euros. In panel (d), the outcome is an indicator for an individual's yearly wage income being lower than 2 "price base amounts", a measure of non-employment in Sweden.

Figure A-5: Impact of Move on Labor Earnings - Sun & Abraham



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 $(t-1)$ using the estimator of Sun and Abraham (2021). 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 left 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).

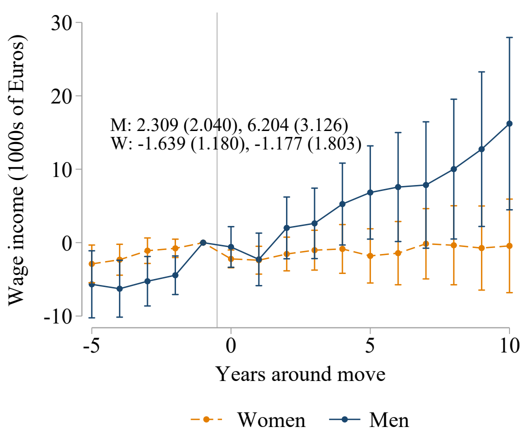
Figure A-6: Relationship between Layoffs and Labor Earnings and Employment



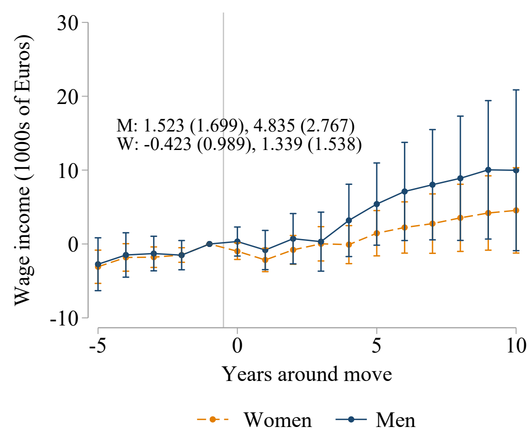
Notes: This figure shows how wage income (in 2017 Euros), days employed, and the number of days an individual received UI benefits change for a laid-off spouse before and after the first layoff. The figures show raw means by gender.

Figure A-7: Male vs. Female Spouse of East German Origin

(a) Only Female Spouse of East German Origin



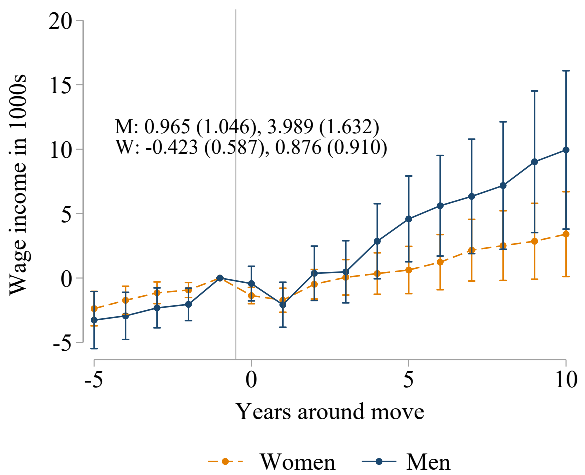
(b) Only Male Spouse of East German Origin



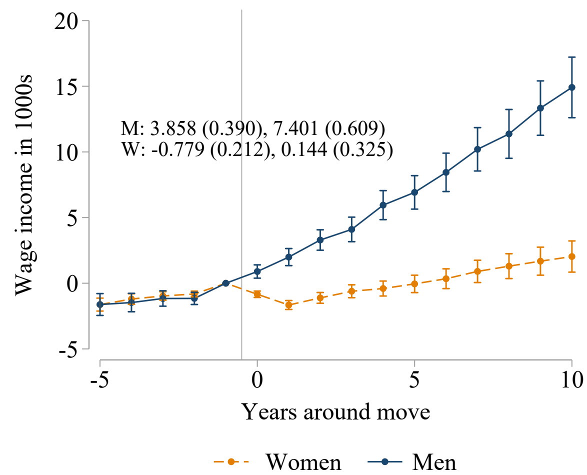
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move (t - 1) for different German subsamples. These subsamples are defined by the place of the first employment of the female (panel (a)) or the male (panel (b)). 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 left 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 A-8: East vs. West German Origin – Reweighted

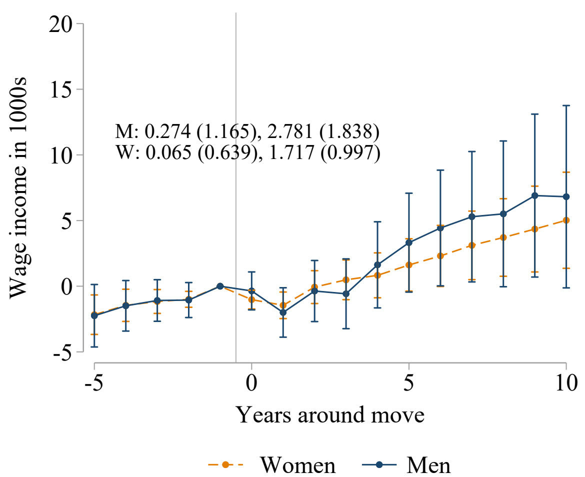
(a) At Least One Spouse of East German Origin



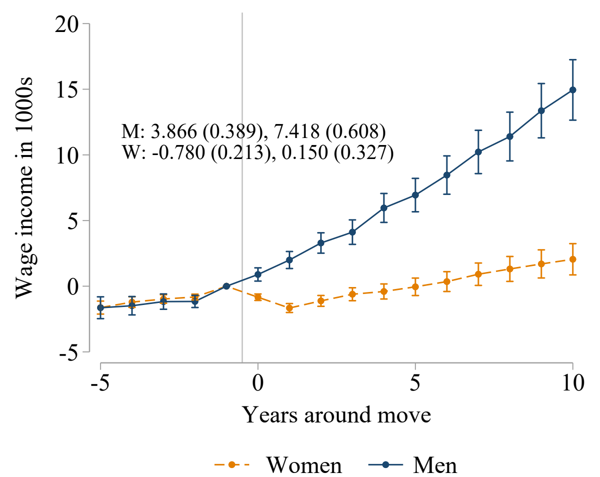
(b) No Spouse of East German Origin



(c) Male Spouse of East German Origin



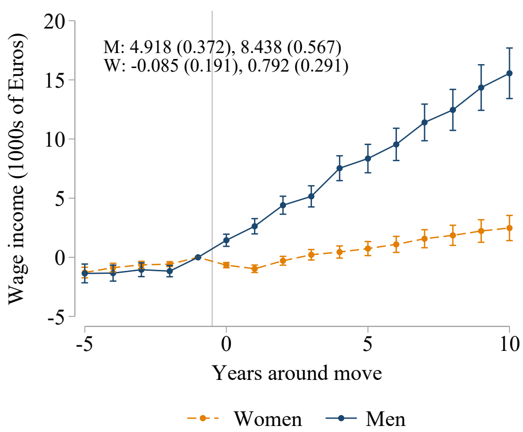
(d) Male spouse Not of East German Origin



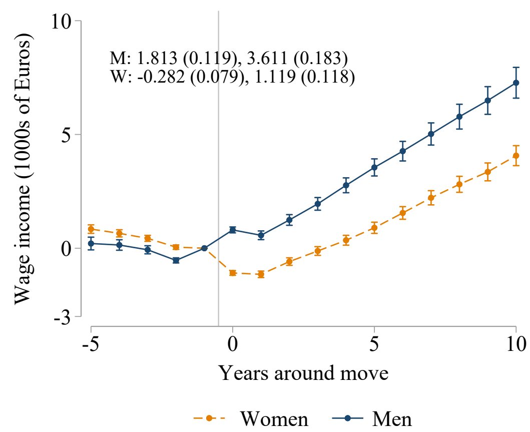
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$) for different German subsamples. These subsamples are defined by place of the first employment of one of the spouses or the male. We reweight couples in panel (b) and (d) to couples in (a) and (c) by the predicted female share of HH income in $t+4$. 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 left 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 A-9: Impact of Move on Wage Income Using Log-Linear Prediction Model

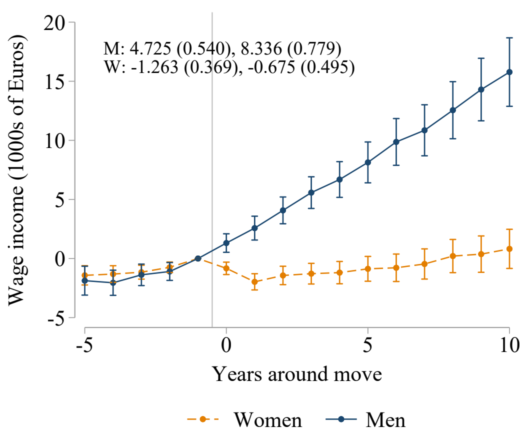
(a) $\hat{s} < 42\%$, Germany



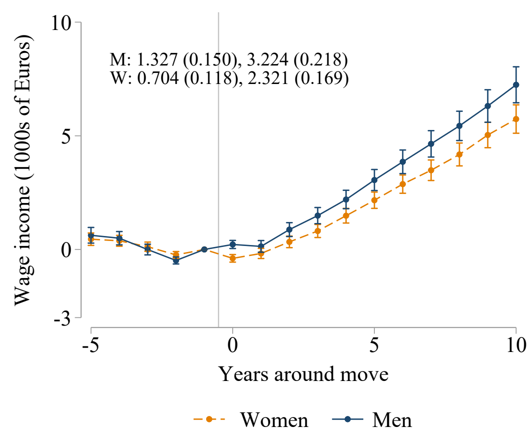
(b) $\hat{s} < 43\%$, Sweden



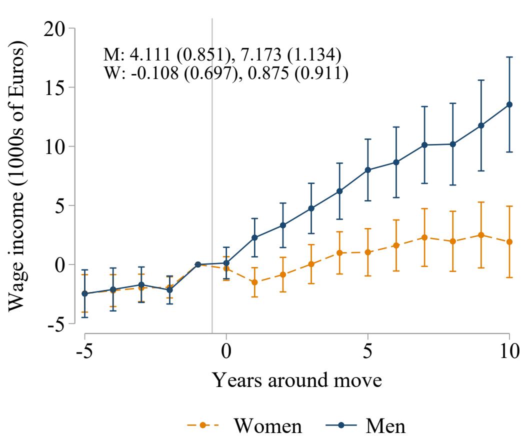
(c) $42\% \leq \hat{s} < 50\%$, Germany



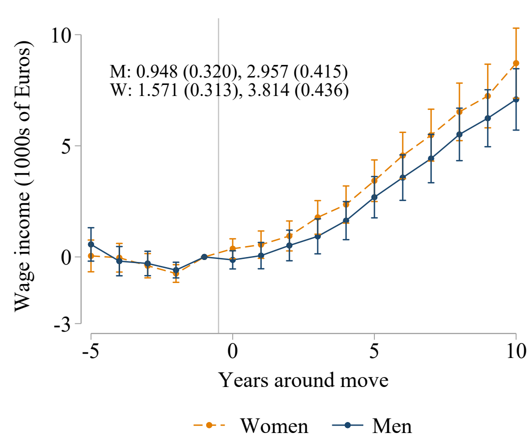
(d) $43\% \leq \hat{s} < 50\%$, Sweden



(e) $\hat{s} \geq 50\%$, Germany

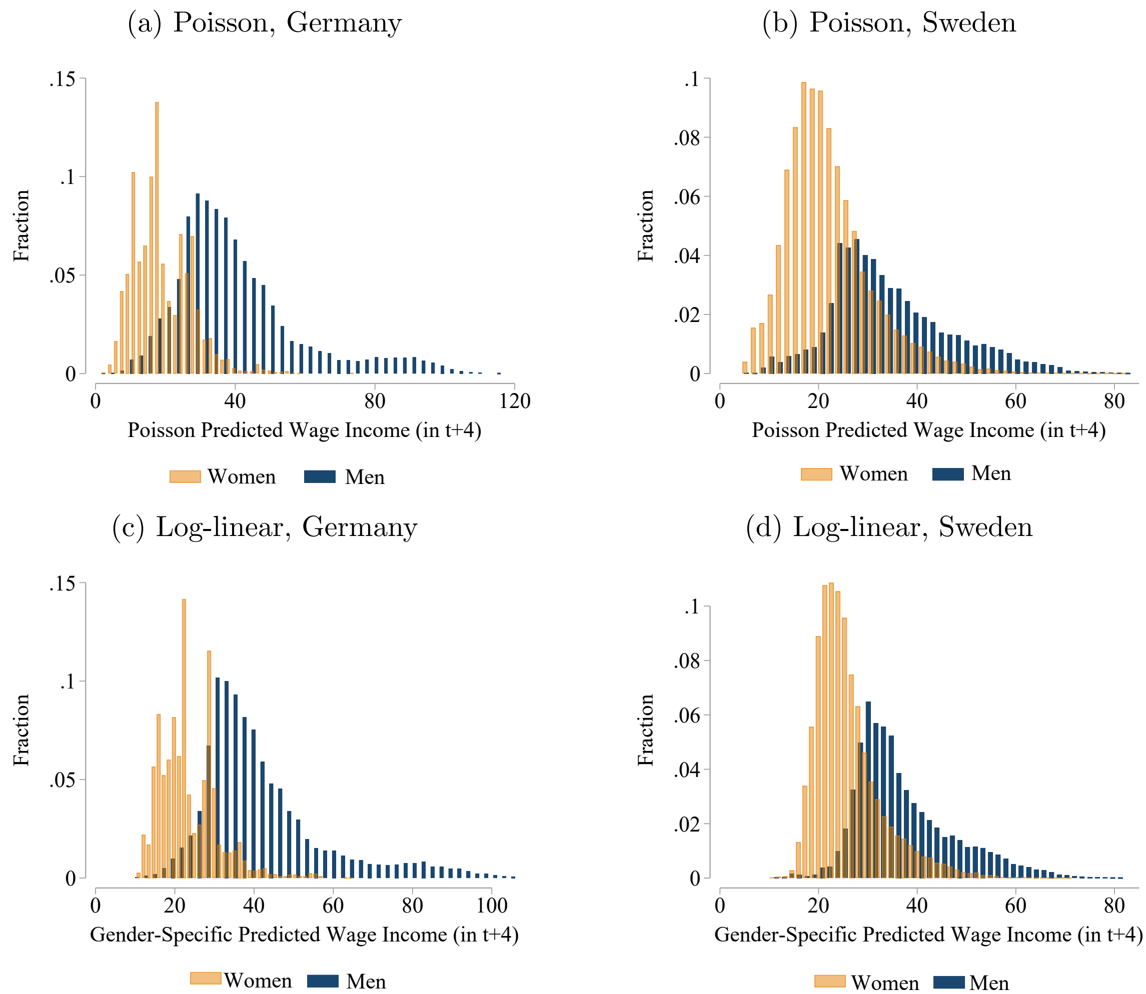


(f) $\hat{s} \geq 50\%$, Sweden



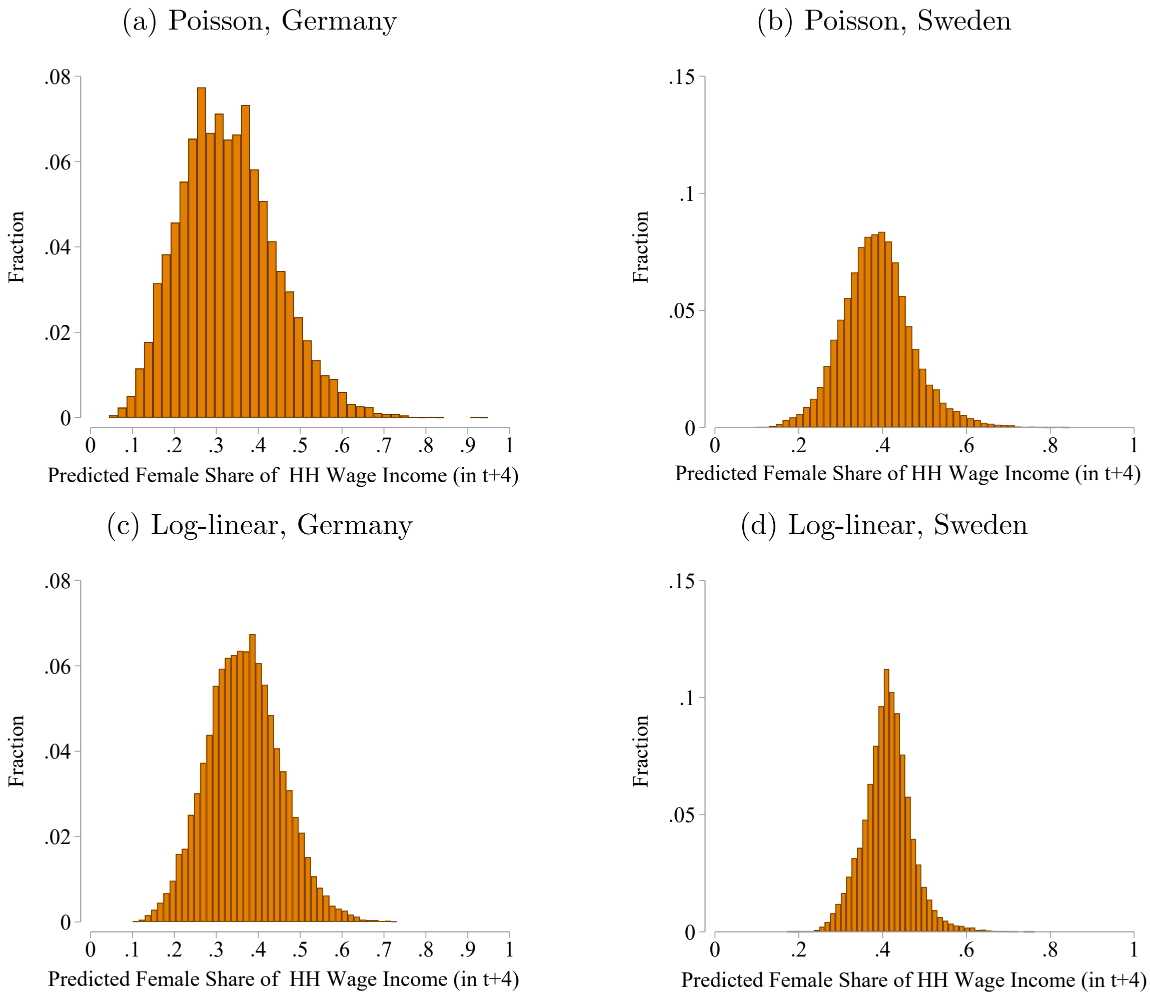
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move $(t-1)$. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions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

Figure A-10: Gender-specific Predicted Wage Income, Movers



Notes: This figure displays histograms of predicted wage income by gender for each country for the movers samples. Panels (a) and (b) show predicted earnings using a Poisson model, which includes 0 earnings. These predictions are calculated regressing individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. Predicted earnings in panels (c) and (d) 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.

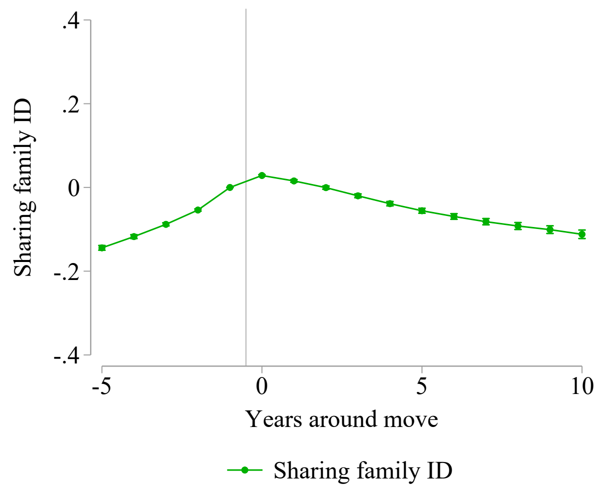
Figure A-11: Gender-specific Predicted Female Share of HH Income, Movers



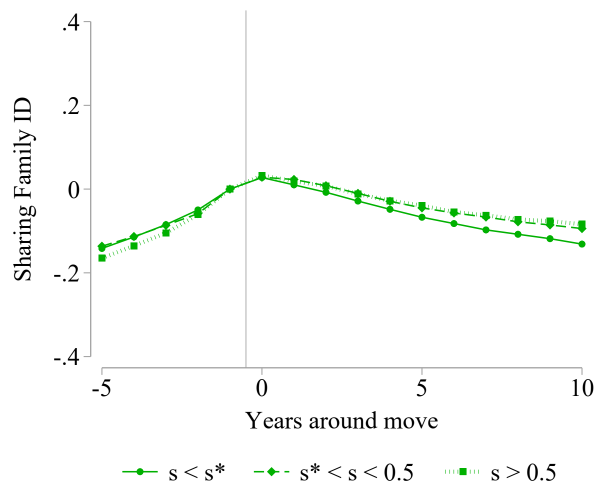
Notes: This figure displays histograms of predicted female share of household income by country for the movers samples. Predicted earnings in panels (a) and (b) are calculated using a poisson model that includes 0 earnings. These predictions are calculated regressing individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. Predicted earnings in panels (c) and (d) 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 A-12: Couple Stability in Sweden

(a) Full Sample



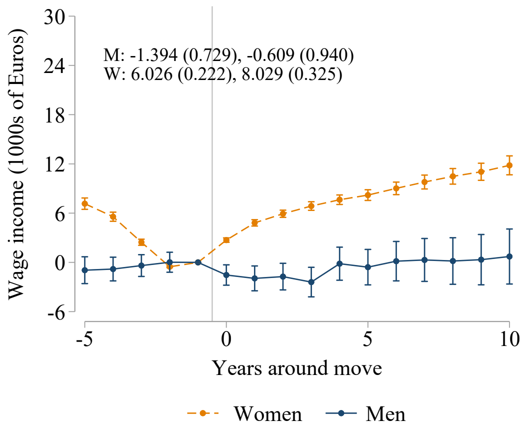
(b) Estimates by Predicted Female Share of HH Income



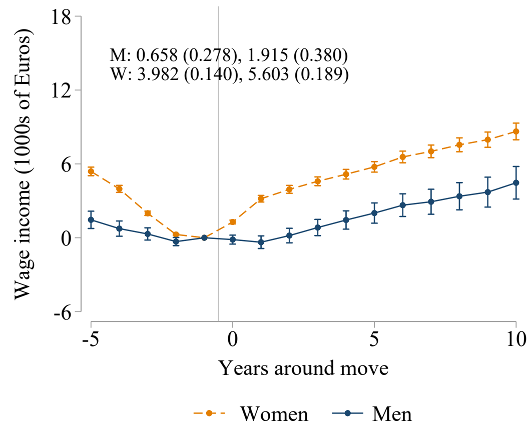
Notes: This figure displays the event study results that estimate the effect of moving on couple stability in each year relative to the year before the move $(t-1)$. Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the household level. The regressions are run at the household level, such that the control variables are used from men and women. Couple stability is measured using an indicator for whether a couple is sharing a joint family ID or not. A couple is sharing the same family ID if they are registered at the same address, and are either married and/or have a joint child.

Figure A-13: Impact of Move on Wage Income, by Actual Female Share of HH Income

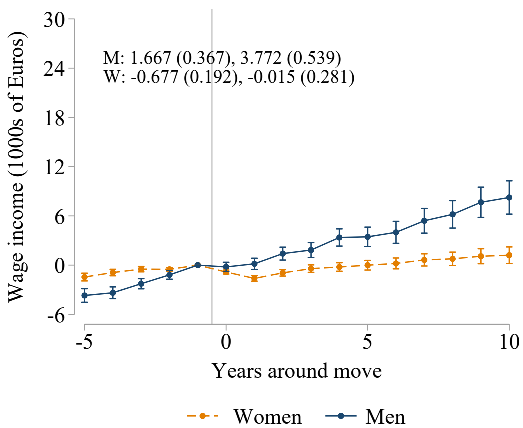
(a) $s < 3\%$, Germany



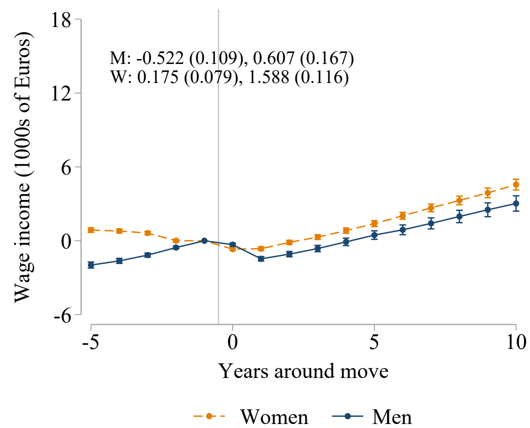
(b) $s < 1\%$, Sweden



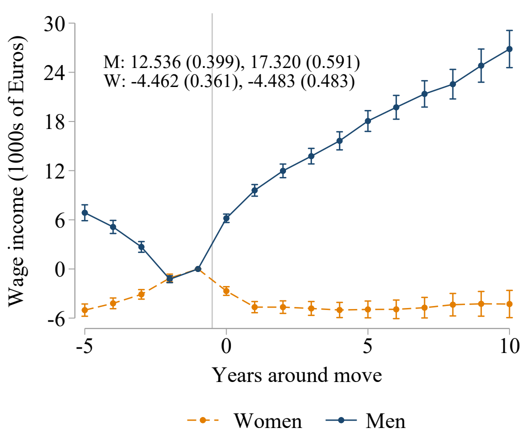
(c) $3\% \leq s < 50\%$, Germany



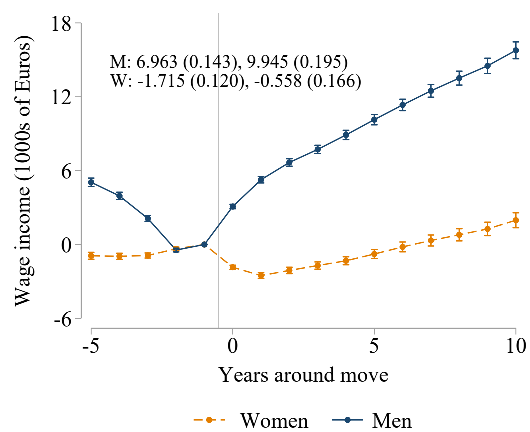
(d) $1\% \leq s < 50\%$, Sweden



(e) $s \geq 50\%$, Germany



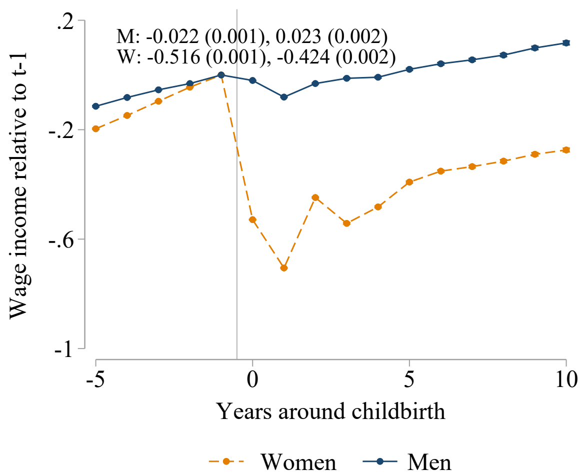
(f) $s \geq 50\%$, Sweden



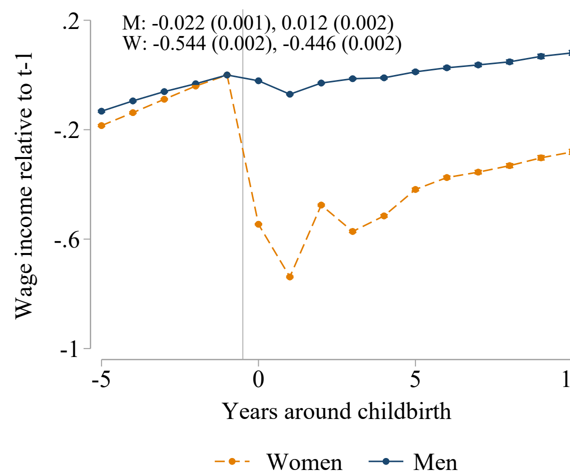
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper left 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). The actual female share of household income is calculated as the average actual female share in $t-2$ and $t-1$. s^* is chosen so that the actual female share of HH income in $s \geq 0.5$ (panel (c)) and $s^* \leq s < 0.5$ (panel (b)) is symmetrically distributed around 0.5.

Figure A-14: Child Penalty - Sweden

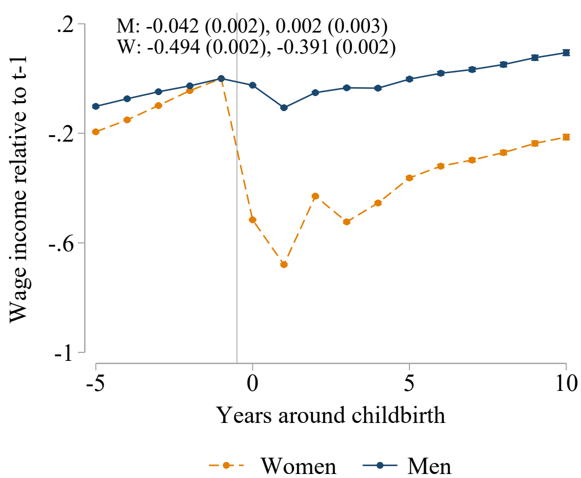
(a) Full Sample



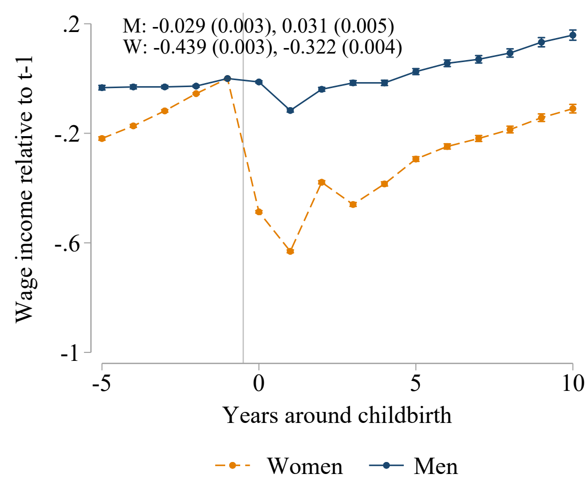
(b) $\hat{s} < 41\%$



(c) $41\% \leq \hat{s} < 50\%$

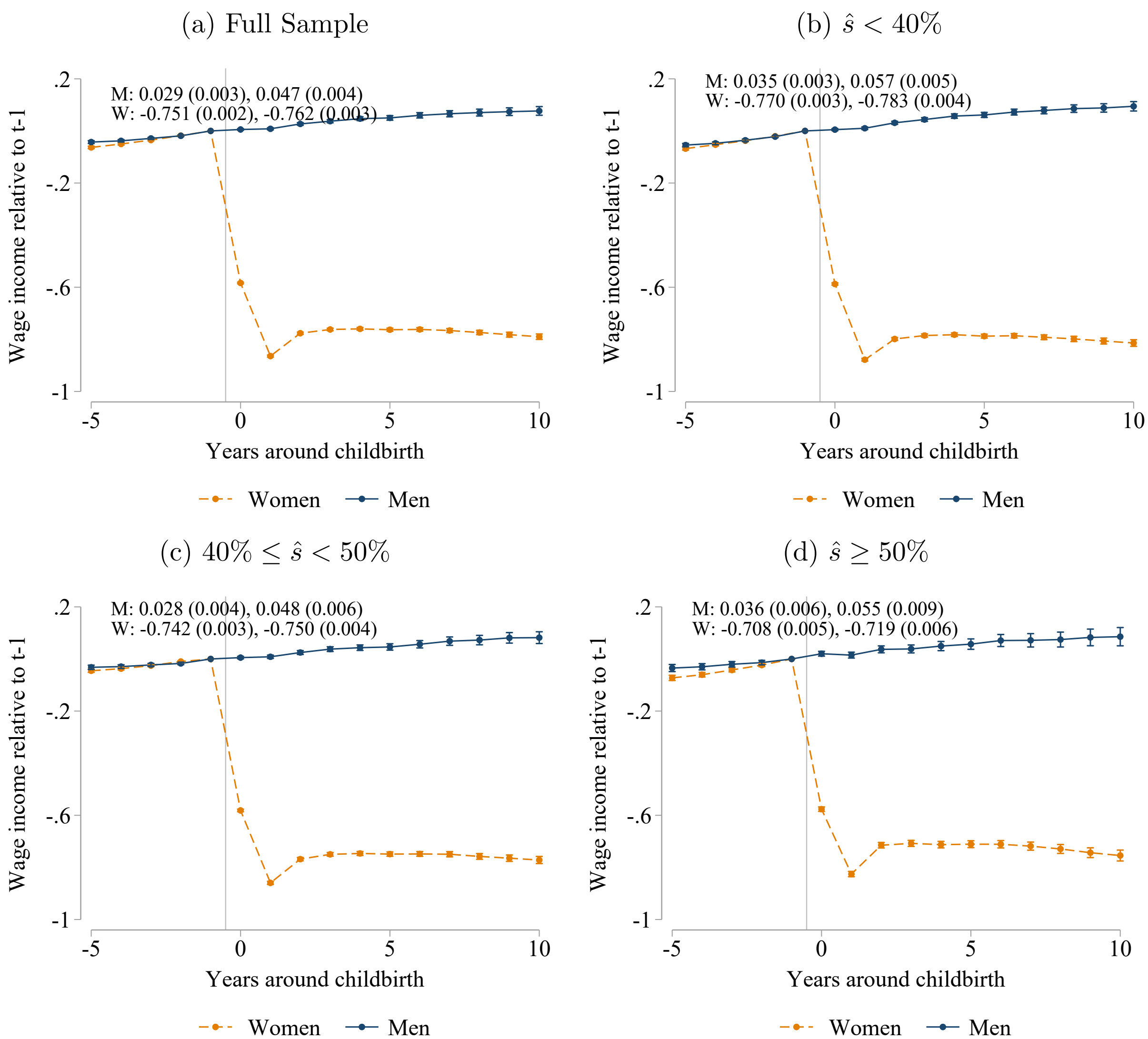


(d) $\hat{s} \geq 50\%$



Notes: This figure displays the event study results that estimate the proportional effect of childbirth on wage income in each year relative to the year before the childbirth ($t-1$). 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 left 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 running a Poisson regression of individual income on experience indicators, and education level interacted with field of study. Panel (a) displays child penalty estimates for the full sample. Panels (b)-(d) display results for subsample splits by predicted female share of HH income, respectively.

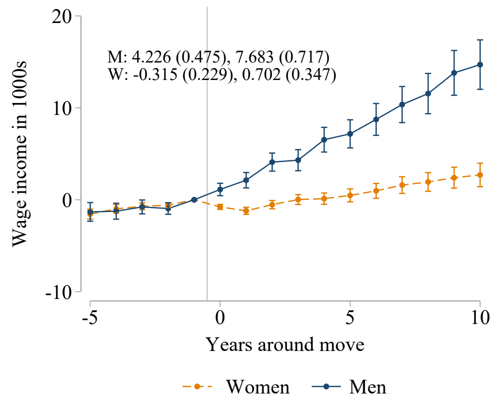
Figure A-15: Child Penalty - Germany



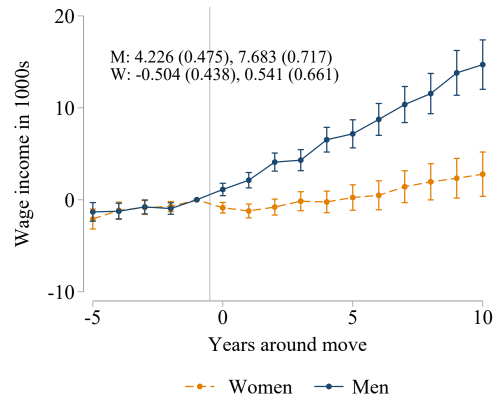
Notes: This figure displays the event study results that estimate the proportional effect of childbirth on wage income in each year relative to the year before the childbirth ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper left corner of each figure are 6 and 11-year averages of the post-birth 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 running a Poisson regression of individual income on experience indicators, and education level interacted with field of study. Panel (a) displays child penalty estimates for the full sample. Panels (b)-(d) display results for subsample splits by predicted female share of HH income, respectively.

Figure A-16: Occupation-weighted Impact of Move on Wage Income in Germany (4-digit)

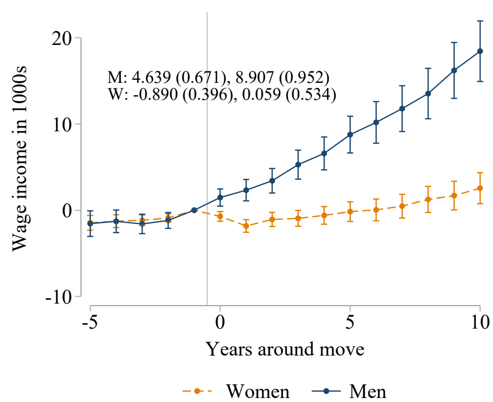
(a) $\hat{s} < 39\%$, Unweighted



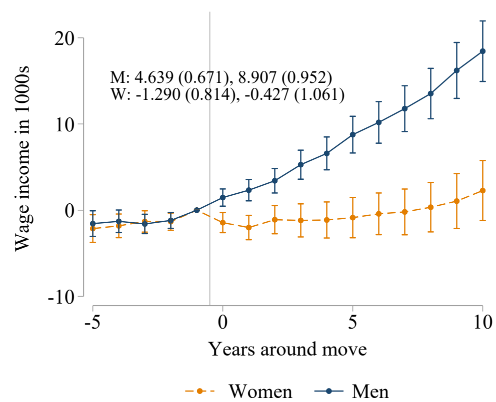
(b) $\hat{s} < 39\%$, Weighted



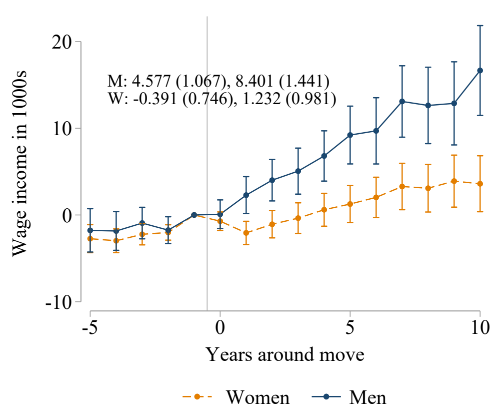
(c) $39\% \leq \hat{s} < 50\%$, Unweighted



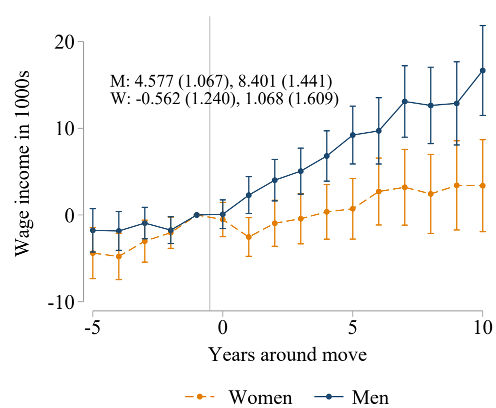
(d) $39\% \leq \hat{s} < 50\%$, Weighted



(e) $\hat{s} \geq 50\%$, Unweighted

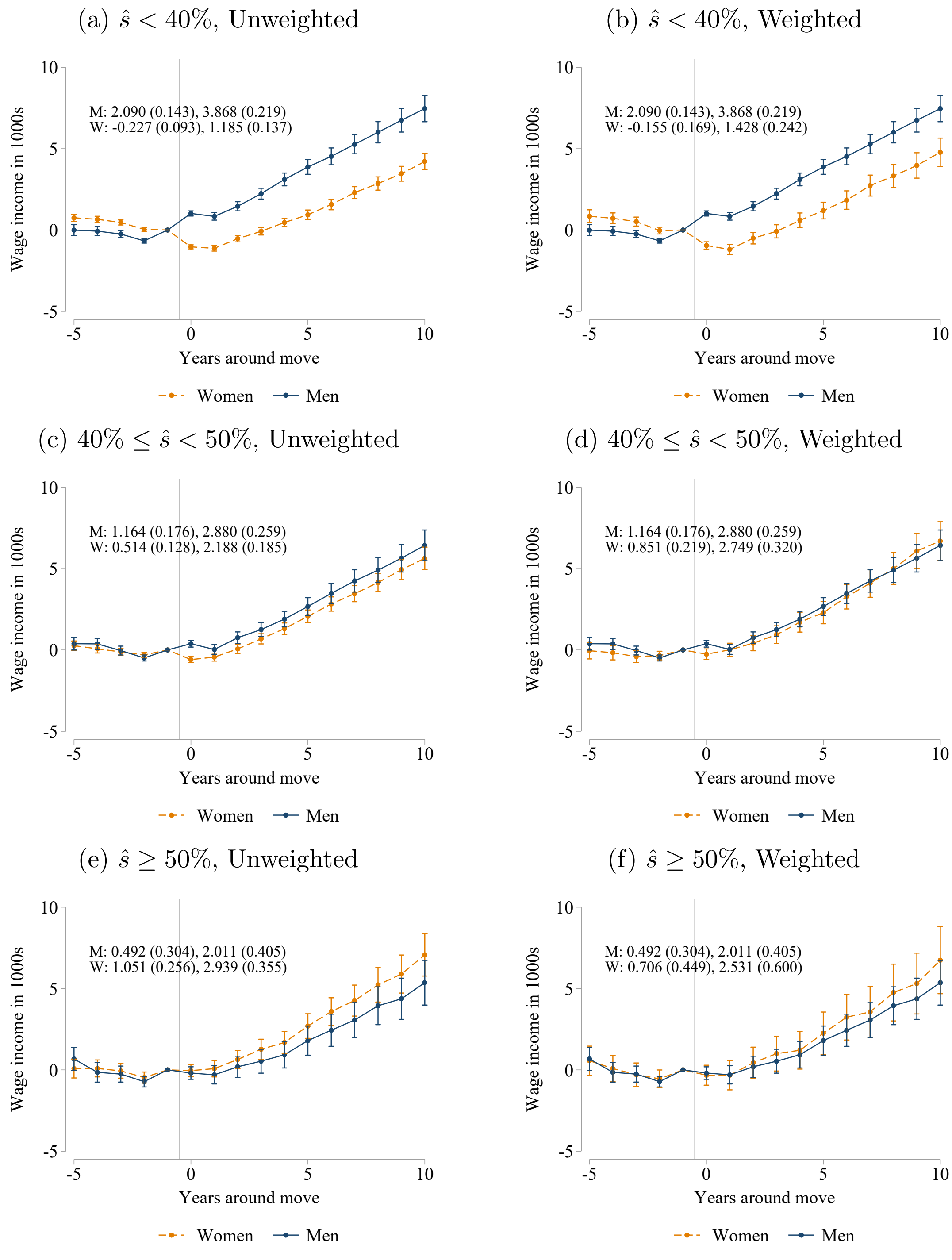


(f) $\hat{s} \geq 50\%$, Weighted



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 left 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 running a Poisson regression of individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. In panel (b), (d), and (f), we re-weight the sample so that women have the same 4-digit occupation distribution as men.

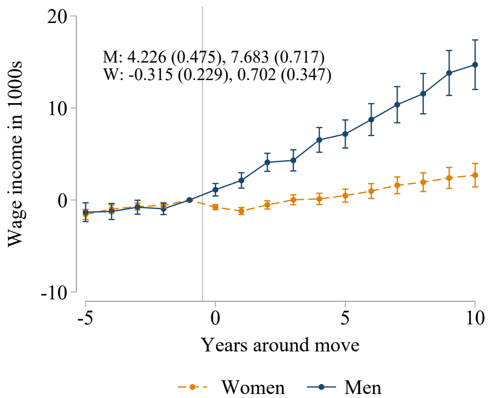
Figure A-17: Occupation-weighted Impact of Move on Wage Income in Sweden



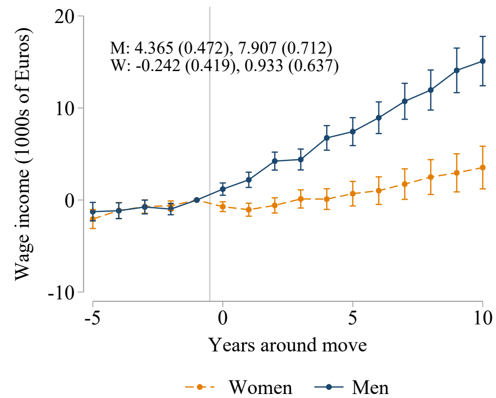
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper left 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 running a Poisson regression of individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. In panel (b), (d), and (f), we re-weight the sample so that women have the same occupation distribution as men. We proxy occupation by education×industry, as there is no occupation information in the Swedish data.

Figure A-18: Occupation-weighted Impact of Move on Wage Income in Germany (3-digit)

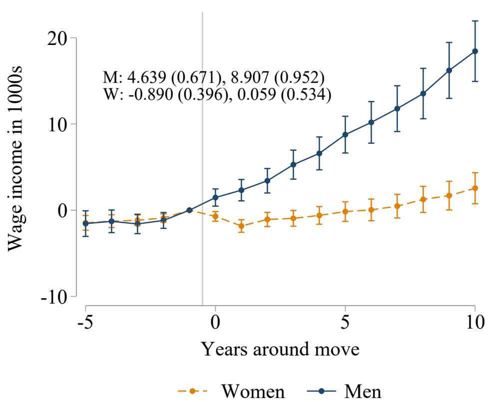
(a) $\hat{s} < 39\%$, Unweighted



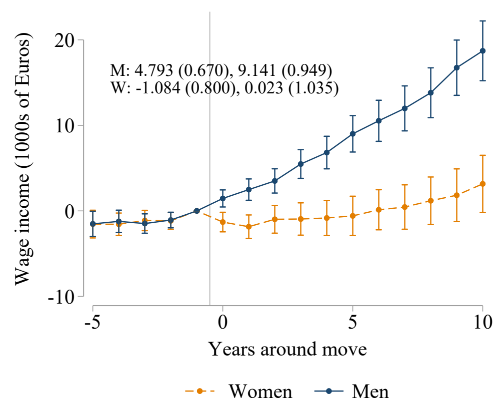
(b) $\hat{s} < 39\%$, Weighted



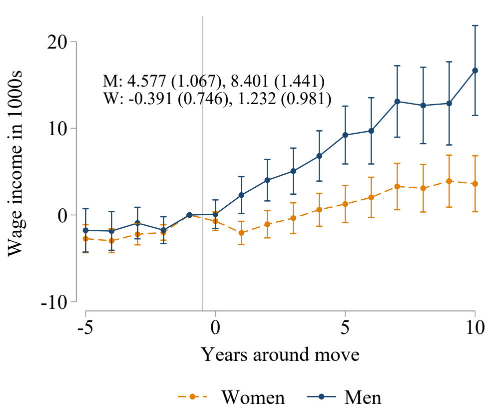
(c) $39\% \leq \hat{s} < 50\%$, Unweighted



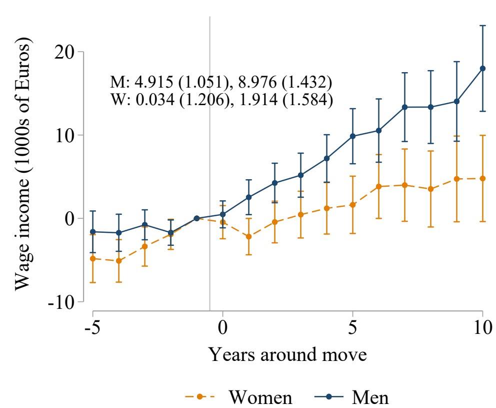
(d) $39\% \leq \hat{s} < 50\%$, Weighted



(e) $\hat{s} \geq 50\%$, Unweighted

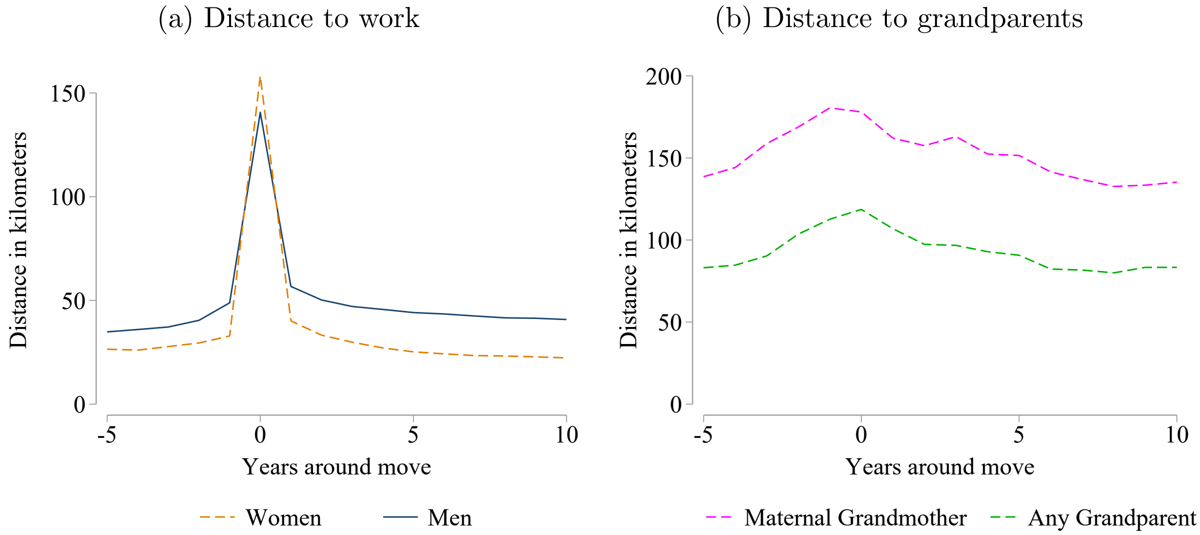


(f) $\hat{s} \geq 50\%$, Weighted



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 left 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 running a Poisson regression of individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. In panel (b), (d), and (f), we re-weight the sample so that women have the same 3-digit occupation distribution as men.

Figure A-19: Amenities (Sweden)



Notes: Panel (a) displays the distance to the job by gender. Panel (b) displays the distance to the closest grandparent and distance to the maternal grandmother. Grandparents are defined as the spouses' parents, regardless of the couple having children or not. All distances are reported in kilometers.

Table A-1: Summary Statistics using Actual vs. Placebo Layoffs, Germany

	Male Layoff				Female Layoff			
	True Layoff		Placebo Layoff		True Layoff		Placebo Layoff	
	Men	Women	Men	Women	Men	Women	Men	Women
Age	38.37	36.62	38.43	36.65	40.89	38.35	40.51	37.96
	(4.83)	(5.66)	(4.83)	(5.65)	(5.91)	(4.98)	(6.14)	(5.27)
Compulsory schooling	0.01	0.02	0.00	0.01	0.01	0.01	0.01	0.00
	(0.09)	(0.15)	(0.06)	(0.12)	(0.09)	(0.10)	(0.07)	(0.07)
High school	0.09	0.09	0.06	0.07	0.06	0.09	0.05	0.06
	(0.29)	(0.29)	(0.23)	(0.25)	(0.23)	(0.28)	(0.22)	(0.25)
Vocational training	0.76	0.78	0.73	0.79	0.78	0.79	0.75	0.78
	(0.43)	(0.41)	(0.45)	(0.41)	(0.41)	(0.41)	(0.44)	(0.41)
College degree	0.14	0.10	0.21	0.13	0.15	0.11	0.20	0.15
	(0.35)	(0.31)	(0.41)	(0.33)	(0.36)	(0.31)	(0.40)	(0.36)
Wage income	44.17	16.63	58.06	16.79	41.36	28.00	47.46	32.01
(1000s EUR)	(27.76)	(17.32)	(35.78)	(18.56)	(32.20)	(15.26)	(36.77)	(18.65)
Employed	1.00	0.84	1.00	0.81	0.93	1.00	0.93	1.00
	(0.00)	(0.37)	(0.00)	(0.39)	(0.26)	(0.00)	(0.26)	(0.00)
Unemp. benefits	0.63	0.28	0.04	0.17	0.43	0.45	0.27	0.03
(1000s EUR)	(1.66)	(1.15)	(0.45)	(0.91)	(1.70)	(1.21)	(1.37)	(0.33)
Days receiving	16.93	16.89	1.04	9.46	15.93	18.53	9.14	1.17
UI benefits (per year)	(41.72)	(64.91)	(11.80)	(47.33)	(59.40)	(45.65)	(44.38)	(12.25)
At least 1 child	0.59	0.59	0.63	0.63	0.48	0.48	0.56	0.56
	(0.49)	(0.49)	(0.48)	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)
Non-native	0.09	0.07	0.06	0.06	0.06	0.05	0.05	0.05
	(0.29)	(0.26)	(0.23)	(0.23)	(0.23)	(0.23)	(0.21)	(0.21)
Observations	6177	6177	97960	97960	4145	4145	47540	47540

Notes: This table displays means and standard deviations (in parentheses) for the listed variables in the period before the layoff ($t-1$) for the job layoffs sample. Columns 1–2 show the characteristics for each member of a couple when the man is laid off. Columns 3–4 show the same but for a placebo layoff of the man. Columns 5–6 show the same but when the woman is laid off, and Columns 7–8 for a placebo layoff of the woman. Wage income and other benefits are measured in 2017 Euros.

Table A-2: Summary Statistics using Actual vs. Placebo Layoffs, Sweden

	Male Layoff				Female Layoff			
	True Layoff		Placebo Layoff		True Layoff		Placebo Layoff	
	Men	Women	Men	Women	Men	Women	Men	Women
Age	37.49	35.90	36.87	35.01	40.01	37.41	39.24	36.76
	(4.95)	(5.63)	(5.12)	(5.84)	(6.20)	(5.05)	(6.45)	(5.20)
Compulsory schooling	0.11	0.08	0.13	0.10	0.15	0.09	0.15	0.09
	(0.31)	(0.28)	(0.33)	(0.31)	(0.36)	(0.29)	(0.36)	(0.28)
High school	0.55	0.53	0.55	0.51	0.54	0.55	0.54	0.49
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Vocational training	0.12	0.03	0.05	0.03	0.06	0.04	0.04	0.03
	(0.32)	(0.18)	(0.22)	(0.17)	(0.24)	(0.20)	(0.21)	(0.16)
Some college	0.06	0.15	0.07	0.15	0.06	0.11	0.07	0.13
	(0.23)	(0.36)	(0.25)	(0.35)	(0.25)	(0.31)	(0.26)	(0.34)
College degree	0.17	0.20	0.20	0.21	0.19	0.21	0.19	0.26
	(0.37)	(0.40)	(0.40)	(0.41)	(0.39)	(0.41)	(0.39)	(0.44)
Wage income	38.27	17.41	35.80	17.58	32.77	25.45	31.47	24.74
(1000s EUR)	(16.12)	(13.51)	(13.74)	(12.76)	(19.15)	(12.15)	(17.74)	(10.34)
Employed	1.00	0.90	1.00	0.91	0.93	1.00	0.93	1.00
	(0.00)	(0.30)	(0.00)	(0.28)	(0.25)	(0.00)	(0.25)	(0.00)
Unemp. benefits	0.44	0.73	0.13	0.76	0.54	0.47	0.54	0.22
(1000s EUR)	(1.72)	(2.16)	(0.93)	(2.19)	(2.16)	(1.64)	(2.12)	(1.05)
Days receiving	11.49	15.33	2.73	16.14	11.88	9.86	12.11	2.70
UI benefits (per year)	(39.25)	(48.21)	(20.06)	(50.04)	(46.88)	(35.75)	(46.33)	(18.93)
At least 1 child	0.91	0.92	0.80	0.80	0.89	0.90	0.80	0.81
	(0.28)	(0.28)	(0.40)	(0.40)	(0.31)	(0.31)	(0.40)	(0.39)
Non-native	0.10	0.11	0.09	0.10	0.10	0.09	0.09	0.09
	(0.30)	(0.31)	(0.29)	(0.30)	(0.30)	(0.29)	(0.28)	(0.29)
Observations	8050	8050	140007	140007	6767	6767	108739	108739

Notes: This table displays means and standard deviations (in parentheses) for the listed variables in the period before the layoff ($t-1$) for the job layoffs sample. Columns 1–2 show the characteristics for each member of a couple when the man is laid off. Columns 3–4 show the same but for a placebo layoff of the man. Columns 5–6 show the same but when the woman is laid off, and Columns 7–8 for a placebo layoff of the woman. Wage income and other benefits are measured in 2017 Euros.

Table A-3: Summary Statistics by Predicted Female Share of HH Income, Germany

	$\hat{s} < 0.39$		$0.39 \leq \hat{s} < 0.5$		$\hat{s} \geq 0.5$	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)
Age	36.54	34.04	35.65	33.63	35.29	33.49
	(5.84)	(5.90)	(6.40)	(6.35)	(7.02)	(6.27)
Compulsory schooling	0.01	0.02	0.01	0.01	0.04	0.01
	(0.08)	(0.15)	(0.11)	(0.11)	(0.18)	(0.09)
High school	0.04	0.07	0.05	0.05	0.06	0.05
	(0.20)	(0.25)	(0.21)	(0.22)	(0.24)	(0.22)
Vocational training	0.60	0.71	0.66	0.71	0.59	0.61
	(0.49)	(0.45)	(0.47)	(0.45)	(0.49)	(0.49)
College	0.36	0.20	0.28	0.23	0.31	0.33
	(0.48)	(0.40)	(0.45)	(0.42)	(0.46)	(0.47)
Wage income (1000s EUR)	49.16	17.65	40.29	26.26	37.07	31.09
	(41.30)	(20.55)	(34.85)	(24.33)	(35.63)	(26.24)
Employed	0.90	0.78	0.88	0.85	0.85	0.86
	(0.30)	(0.41)	(0.32)	(0.36)	(0.36)	(0.34)
UI benefits (1000s EUR)	0.57	0.35	0.59	0.37	0.55	0.32
	(2.04)	(1.28)	(1.94)	(1.44)	(1.78)	(1.30)
Days receiving	18.20	19.22	20.78	18.16	21.00	15.38
UI benefits (per year)	(61.70)	(65.79)	(66.05)	(65.32)	(65.12)	(59.24)
At least 1 child	0.71	0.71	0.50	0.50	0.49	0.49
	(0.45)	(0.45)	(0.50)	(0.50)	(0.50)	(0.50)
Non-native	0.07	0.08	0.07	0.07	0.11	0.08
	(0.25)	(0.27)	(0.26)	(0.26)	(0.31)	(0.27)
Predicted earnings in t+4	44.93	16.58	31.11	24.10	22.48	28.69
	(18.56)	(7.00)	(9.08)	(6.88)	(7.81)	(8.98)
Predicted female share	0.27	0.27	0.44	0.44	0.56	0.56
of HH income in t+4	(0.07)	(0.07)	(0.03)	(0.03)	(0.06)	(0.06)
Observations	14418	14418	4036	4036	1499	1499

Notes: This table displays means and standard deviations (in parentheses) for different outcomes in the period before the move ($t-1$) in Germany. Wage income and other benefits are measured in 2017 Euros.

Table A-4: Summary Statistics by Predicted Female Share of HH Income, Sweden

	$\hat{s} < 0.4$		$0.4 \leq \hat{s} < 0.5$		$\hat{s} \geq 0.5$	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)
Age	34.26	31.64	35.59	34.08	37.64	35.90
	(6.34)	(6.27)	(6.73)	(5.97)	(7.91)	(6.06)
Compulsory schooling	0.10	0.18	0.17	0.05	0.24	0.04
	(0.29)	(0.39)	(0.37)	(0.21)	(0.43)	(0.21)
High school	0.49	0.46	0.47	0.44	0.44	0.29
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.45)
Vocational training	0.08	0.05	0.06	0.04	0.10	0.04
	(0.27)	(0.21)	(0.24)	(0.20)	(0.29)	(0.20)
Some college	0.06	0.12	0.08	0.12	0.10	0.12
	(0.25)	(0.32)	(0.27)	(0.32)	(0.31)	(0.33)
College degree	0.28	0.19	0.22	0.35	0.12	0.50
	(0.45)	(0.40)	(0.42)	(0.48)	(0.33)	(0.50)
Wage income (1000s EUR)	29.48	13.66	27.85	19.60	24.10	22.46
	(20.03)	(12.36)	(18.95)	(14.92)	(18.75)	(17.33)
Employed	0.89	0.81	0.88	0.87	0.83	0.87
	(0.32)	(0.40)	(0.32)	(0.33)	(0.37)	(0.34)
Unemp. benefits (1000s EUR)	0.92	1.06	0.90	0.90	0.87	0.87
	(2.73)	(2.62)	(2.72)	(2.54)	(2.65)	(2.61)
Days receiving	25.74	27.67	23.47	21.99	27.29	21.65
UI benefits (per year)	(67.29)	(66.17)	(63.79)	(60.22)	(69.76)	(61.67)
At least 1 child	0.70	0.71	0.61	0.59	0.57	0.55
	(0.46)	(0.46)	(0.49)	(0.49)	(0.50)	(0.50)
Non-native	0.14	0.17	0.13	0.13	0.27	0.17
	(0.35)	(0.38)	(0.34)	(0.33)	(0.44)	(0.38)
Predicted earnings in t+4	37.37	18.64	32.16	25.47	24.90	31.14
	(12.24)	(6.42)	(11.13)	(8.97)	(9.57)	(11.14)
Predicted female share	0.33	0.33	0.44	0.44	0.56	0.56
of HH income in t+4	(0.05)	(0.05)	(0.03)	(0.03)	(0.05)	(0.05)
Observations	28283	28283	14934	14934	4096	4096

Notes: This table displays means and standard deviations (in parentheses) for different outcomes in the period before the move ($t-1$) in Sweden. Wage income and other benefits are measured in 2017 Euros.

Table A-5: Sensitivity Analysis for Model Parameter Estimates

		Change in migration rate, M				
	Baseline model	M ×0.5	M ×2	No Measurement error in $\hat{s}$	Two-step Estimation	Correlated migration returns
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Germany						
Mean returns to to migration, μ_r	-0.145 (0.081)	-0.127 (0.067)	-0.165 (0.096)	-0.095 (0.081)	-0.142	-0.074
Std. deviation in the returns to migration, σ_r	0.127 (0.049)	0.101 (0.037)	0.163 (0.066)	0.107 (0.049)	0.126	0.089
Household mobility cost, c	2.113 (0.893)	2.634 (0.694)	1.365 (1.196)	2.761 (0.893)	2.146	2.713
Husband-wife covariance in returns to migration, $\sigma_{m,f}$						-0.002
Relative weight on woman's income, β	0.481 (0.144)	0.495 (0.133)	0.465 (0.156)	0.563 (0.144)	0.476	0.503
Panel B: Sweden						
Mean returns to to migration, μ_r	-0.034 (0.033)	-0.020 (0.029)	-0.050 (0.036)	-0.021 (0.033)	-0.028	-0.071
Std. deviation in the returns to migration, σ_r	0.049 (0.024)	0.035 (0.020)	0.069 (0.028)	0.045 (0.024)	0.046	0.069
Household mobility cost, c	1.775 (0.479)	2.260 (0.454)	1.210 (0.507)	2.017 (0.479)	1.872	1.362
Husband-wife covariance in returns to migration, $\sigma_{m,f}$						0.0008
Relative weight on woman's income, β	0.820 (0.095)	0.760 (0.109)	0.821 (0.084)	0.844 (0.095)	0.771	0.815

Notes: Column (1) shows the model-based estimates for both countries using a simple equal-weighted minimum distance estimator. The moments used for estimation are the average migration rate and the effects of moving for $s^* \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$, as reported in Table 3. To evaluate sensitivity, Columns (2) and (3) vary the migration rate. Column (4) displays the results while accounting for measurement error in the predicted female share of household income. Column (5) shows the results using a two-step estimation approach. Lastly, Column (6) shows the model-based estimates allowing for covariance between male and female spouse returns to moving shock. Note that s^* differs by country - 0.39 for Germany and 0.40 for Sweden.

Table A-6: Simulated Moments Restricting to $\beta = 1$

Predicted Female Share of Household Income, $\hat{s}$	Germany Men (1)	Germany Women (2)	Sweden Men (3)	Sweden Women (4)
Targeted Moments:				
$\hat{s} \geq 50$	2.975	1.919	0.384	1.356
$s^* \leq \hat{s} < 0.50$	5.144	-1.015	0.998	0.552
Household migration rate	0.037		0.041	
χ^2 [p-value]	12.164 [<0.001]		3.512 [0.061]	
Untargeted Moment: $\hat{s} < s^*$	8.486	-3.239	1.607	0.030

Notes: This table presents results similar to Panel B of Table 5, where we set $\beta = 1$ and re-estimate the other model parameters. χ^2 is a goodness-of-fit statistic. Note that $s^* = 0.39$ for Germany, and $s^* = 0.40$ for Sweden. Notes in Table 3 explain how s^* is chosen.

Table A-7: Restricted Model Parameter Estimates

	Germany (1)	Sweden (2)
Mean returns to migration, μ_r	-0.822	-0.088
	(0.089)	(0.032)
Standard deviation in the returns to migration, σ_r	0.542	0.081
	(0.051)	(0.022)
Mean household mobility cost, μ_c	0.470	1.130
	(1.140)	(0.382)
Relative weight on woman's income compared to man's income, β	1.00	1.00

Notes: This table 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 $s^* \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 3. Parameters used here were the same used in the main text in Table 7, which are reported in Table 3. Note that s^* differs by country - 0.39 for Germany and 0.40 for Sweden.

Table A-8: Impact of Layoffs on Moving Probability – Re-weighted Sample

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Male Spouse Laid Off	0.62	0.43	0.45	1.34	1.52	1.40
	(0.22)	(0.23)	(0.23)	(0.25)	(0.25)	(0.25)
Female Spouse Laid Off	0.16	0.19	0.21	0.58	0.71	0.73
	(0.29)	(0.29)	(0.27)	(0.379)	(0.38)	(0.39)
Age FE		✓	✓		✓	✓
CZ FE			✓			✓
N (Men Laid Off)	3581	3581	3581	5508	5508	5508
N (Women Laid Off)	3532	3532	3532	6263	6263	6263
Mean	0.790	0.790	0.790	1.570	1.570	1.570
M=W p-value	0.177	0.509	0.464	0.082	0.077	0.138
Observations	111534	111534	111526	198090	198090	198090

Notes: This table displays point estimates and robust standard errors (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. All points estimates and standard errors are multiplied by 100. We reweight couples where the woman has been laid off to couples where the man has been laid off based on pre-layoff occupation. In Sweden, we proxy occupation by education×industry, as there is no occupation information in the Swedish data.

Table A-9: Sensitivity of U-Shape Migration Pattern to Assortative Mating

	$\beta = 1$			$\beta = 0.8$		
Male/Female income variance	$\sigma_M = \sigma_F$	$\sigma_F > \sigma_M$	$\sigma_F > \sigma_M$	$\sigma_M = \sigma_F$	$\sigma_F > \sigma_M$	$\sigma_F > \sigma_M$
Assortative mating	N	N	Y	N	N	Y
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No controls						
$\hat{s}$ (β_1)	-0.543	-0.4625	-0.5066	-0.515	-0.441	-0.496
	(0.017)	(0.010)	(0.008)	(0.017)	(0.010)	(0.008)
$\hat{s}^2$ (β_2)	0.535	0.527	0.555	0.441	0.451	0.496
	(0.022)	(0.013)	(0.010)	(0.022)	(0.013)	(0.010)
$-\beta_1/(2\beta_2)$	0.508	0.439	0.456	0.584	0.489	0.5
	(0.005)	(0.002)	(0.002)	(0.010)	(0.003)	(0.003)
p-value of $-\beta_1/(2\beta_2) = 0.5$	[0.164]	[< 0.001]	[< 0.001]	[< 0.001]	[0.001]	[0.869]
Panel B: Income quintile dummies as controls						
$\hat{s}$ (β_1)	-0.388	-0.399	-0.407	-0.345	-0.354	-0.374
	(0.017)	(0.010)	(0.008)	(0.017)	(0.010)	(0.008)
$\hat{s}^2$ (β_2)	0.3788	0.407	0.414	0.287	0.317	0.342
	(0.022)	(0.013)	(0.010)	(0.022)	(0.013)	(0.010)
$-\beta_1/(2\beta_2)$	0.512	0.49	0.492	0.602	0.559	0.547
	(0.008)	(0.004)	(0.003)	(0.017)	(0.007)	(0.005)
p-value of $-\beta_1/(2\beta_2) = 0.5$	[0.113]	[0.016]	[0.005]	[< 0.001]	[< 0.001]	[< 0.001]

Notes: This table displays results from section A.3 - using the quadratic specification as in Foged (2016) to test for $\beta = 1$. Results are reported for $\beta = 1$ and $\beta = 0.8$. Panel A displays results without controls, while Panel B includes controls for income quintile dummy variables. Column (1) shows results with no assortative mating, $\mu_M > \mu_F$, and $\sigma_M = \sigma_W$. Column (2) shows results for the same, but with $\sigma_F > \sigma_M$. Column (3) then allows for assortative mating. Remaining columns show analogous results for $\beta = 0.8$.

Table A-10: Sensitivity of Earnings Effects of Moving to Allowing for Assortative Mating

	$\beta = 1$			$\beta = 0.8$		
Male/Female income variance	$\sigma_M = \sigma_F$	$\sigma_F > \sigma_M$	$\sigma_F > \sigma_M$	$\sigma_M = \sigma_F$	$\sigma_F > \sigma_M$	$\sigma_F > \sigma_M$
Assortative mating	N	N	Y	N	N	Y
	(1)	(2)	(3)	(4)	(5)	(6)
Average change in earnings (conditional on moving) = $E[\Delta y_i \mid \Delta y_M + \beta \Delta y_F > c]$						
Panel A: $E[\hat{s} = 0.5]$						
Men	1.340	1.561	1.647	1.650	1.906	2.016
	(0.037)	(0.043)	(0.050)	(0.035)	(0.040)	(0.048)
Women	1.388	1.523	1.587	1.137	1.205	1.278
	(0.037)	(0.042)	(0.049)	(0.041)	(0.046)	(0.053)
p-value of $M = W$	[0.477]	[0.622]	[0.500]	[< 0.001]	[< 0.001]	[< 0.001]
Panel B: $E[\hat{s} = 0.4]$						
Men	2.194	2.277	2.422	2.406	2.504	2.67
	0.0087	0.011	0.013	0.008	0.0098	0.0125
Women	0.656	0.672	0.719	0.421	0.422	0.447
	0.0074	0.0089	0.011	0.0078	0.0093	0.0116
p-value of $M = W$	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]

Notes: This table presents results from section A.3 - showing the average change in earnings as $\hat{s}$'s distribution shifts - between $E[\hat{s} = 0.5]$ in Panel A and $E[\hat{s} = 0.4]$ in Panel B. Results are reported for $\beta = 1$ and $\beta = 0.8$. Column (1) shows results with no assortative mating, $\mu_M > \mu_F$, and $\sigma_M = \sigma_F$. Column (2) shows results for the same, but with $\sigma_F > \sigma_M$. Column (3) then allows for assortative mating. Remaining columns show analogous results for $\beta = 0.8$.

B Predicted Income Methodology

We use the following earnings prediction model:

$$\begin{aligned} Y_{is}^{g} = & \sum_{k} \alpha_{k}^{g} \times \mathbb{1}[k = e\hat{x}p_{is}] + \sum_{p} \sum_{q} \beta_{pq}^{g} \times \mathbb{1}[p = educlvl_{is}] \times \mathbb{1}[q = educfield_{is}] \\ & + \sum_{y} \nu_{y}^{g} \times \mathbb{1}[s = y] + \theta^{g} Child18_{is} + \epsilon_{is}^{g} \end{aligned} \tag{3}$$

where Y_{is} is individual i's wage income in year s. We include controls for potential experience ($e\hat{x}p$), an indicator for having a child aged 0-18 ($Child18$), college major ($educfield$) interacted with education level ($educlvl$), and year (y).

We estimate the model in Sweden using a 1990-2017 panel with a sample of the population aged 25–54, who are married or cohabiting with joint children. We use education level and field variables on a 3-digit level. In Germany, we estimate the model using a 1995-2021 panel with a sample of married individuals aged 25–54. We do not have college major information so we use the level of education (4 categories) and the first occupation on a 3-digit level.

In the baseline analysis, we focus on *gender-specific* predictions using a Poisson model, so that the regression model above is run on men and women separately. We use a Poisson model to allow for zero wage income. We also report results using a gender-specific log-linear prediction model. In the log-linear prediction model, we drop individuals with a wage income below 2 price base amounts (ca. €8000) per year, which is our preferred proxy for non-employment.

C Model Appendix

C.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 $dx = -ds$.

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

Returning to integral A:

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

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.

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

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.[50]

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

Plugging this back into integral A, we have:

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

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

$$\text{logit}(s) = log\left(\frac{s}{1-s}\right) = \log(s) - \log(1-s)$$

[50] 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 $f(1) = 1$.

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

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 $g(s) = g(1-s)$.

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

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 $X = \mu_r + \varepsilon_{M2}$ and $Y = \mu_r + \varepsilon_{F2}$, where $\varepsilon_{i2} \sim N(0, \sigma_r^2)$. We assume $cov(X, Y) = 0$.

$$\begin{aligned} X &= \mu_r + \varepsilon_{M2} & Y &= \mu_r + \varepsilon_{F2} \\ &\sim N(\mu_r, \sigma_r^2) & &\sim N(\mu_r, \sigma_r^2) \\ (1-s)y_1 X &= (1-s)y_1\mu_r + (1-s)y_1\varepsilon_{M2} & sy_1 Y &= sy_1\mu_r + sy_1\varepsilon_{F2} \\ &\sim N((1-s)y_1\mu_r, ((1-s)y_1\sigma_r)^2) & &\sim N(sy_1\mu_r, (sy_1\sigma_r)^2) \end{aligned} \tag{4}$$

With this substitution, we can rewrite the expectation to be $E[mX - fY \mid mX + fY > c]$, which leads to the following expression:

$$E[mX - fY | mX + fY > c] = m\mu_X - f\mu_Y + \lambda(z)\left[\frac{(m\sigma_X)^2 - (f\sigma_Y)^2}{\sqrt{(m\sigma_X)^2 + (f\sigma_Y)^2 + 2\sigma_{mX,fY}}}\right]$$

$$\begin{aligned} &\text{where } z = \frac{c - m\mu_X - f\mu_Y}{\sqrt{(m\sigma_X)^2 + (f\sigma_Y)^2 + 2\sigma_{mX,fY}}} \\ &= (1-s)\mu_r y_1 - s\mu_r y_1 + \lambda\left(\frac{c - (1-s)\mu_r y_1 - s\mu_r y_1}{\sqrt{((1-s)y_1\sigma_r)^2 + (sy_1\sigma_r)^2}}\right)\left[\frac{((1-s)y_1\sigma_r)^2 - (sy_1\sigma_r)^2}{\sqrt{((1-s)y_1\sigma_r)^2 + (sy_1\sigma_r)^2}}\right] \\ &= \mu_r y_1(1-2s) + \lambda\left(\frac{c - \mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2 + s^2}}\right)\left[\frac{\sigma_r^2 y_1^2[(1-s)^2 - s^2]}{\sigma_r y_1\sqrt{(1-s)^2 + s^2}}\right] \\ &= \mu_r y_1(1-2s) + \lambda\left(\frac{c - \mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2 + s^2}}\right)\left[\frac{\sigma_r y_1(1-2s)}{\sqrt{(1-s)^2 + s^2}}\right] \end{aligned}$$

The expression we end up with is given below:

$$E[X - Y | X + Y > c] = (1-2s)\left[\mu_r y_1 + \lambda\left(\frac{c - \mu_r y_1}{\sigma_r y_1\sqrt{(1-s)^2 + s^2}}\right)\left[\frac{\sigma_r y_1}{\sqrt{(1-s)^2 + s^2}}\right]\right] \tag{5}$$

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 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 (5) 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 $s = 0.5$, $E[\varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2} s y_1 \mid s, \varepsilon_{M2}(1-s)y_1 + \beta \varepsilon_{F2} s y_1 > c] > 0$. We use the following substitutions, where $\varepsilon_{i2} \sim N(0, \sigma_r^2)$:

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

Rewriting the expectation to fit the form, $E[mX - fY \mid mX + bfY > c]$, we plug in our substitutions for mX, fY.

$$E[mX - fY \mid mX + bfY > c] = m\mu_X - f\mu_Y + \lambda(z)\left[\frac{(m\sigma_X)^2 - (bf\sigma_Y)^2 + 2\sigma_{mX,fY}(b-1)}{\sqrt{(m\sigma_X)^2 + (bf\sigma_Y)^2 + 2b\sigma_{mX,fY}}}\right]$$

$$\text{where } z = \frac{c - m\mu_X - bf\mu_Y}{\sqrt{(m\sigma_X)^2 + (bf\sigma_Y)^2 + 2b\sigma_{mX,fY}}}$$

$$= \lambda\left(\frac{c - 0.5y_1\mu_r - \beta 0.5y_1\mu_r}{\sqrt{(0.5y_1\sigma_r)^2 + (\beta 0.5y_1\sigma_r)^2}}\right)\left[\frac{(0.5y_1\sigma_r)^2 - (\beta 0.5y_1\sigma_r)^2}{\sqrt{(0.5y_1\sigma_r)^2 + (\beta 0.5y_1\sigma_r)^2}}\right]$$

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

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

$$E[mX - fY \mid mX + bfY > c] = \lambda\left(\frac{c - 0.5y_1\mu_r(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{0.5y_1\sigma_r(1-\beta^2)}{\sqrt{1+\beta^2}}\right] \tag{6}$$

To prove the proposition, we want to show that the expression above is positive. The Inverse Mills Ratio, $\lambda(\cdot)$, is always greater than zero. And for $0 < \beta < 1$, the numerator in the second term, $0.5y_1\sigma_r(1-\beta^2)$, is in the open interval $(0, 0.5y_1\sigma_r)$. Because $0.5y_1\sigma_r > 0$, we have shown that $E[mX - fY | mX + \beta fY > c] > 0$, 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:

$$\lim_{\beta\to 1} E[mX - fY \mid mX + bfY > c] = \lim_{\beta\to 1}\lambda\left(\frac{c - 0.5y_1\mu_r(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{0.5y_1\sigma_r(1-\beta^2)}{\sqrt{1+\beta^2}}\right]$$

$$= \lambda\left(\frac{c - 0.5y_1\mu_r(1+1)}{0.5y_1\sigma_r\sqrt{1+1^2}}\right)\left[\frac{0.5y_1\sigma_r(1-(1)^2)}{\sqrt{1+1^2}}\right]$$

$$= 0$$

C.2 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 C.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 mX and fY from Equation (4) where $mX \sim N((1-s)\mu_r y_1, ((1-s)y_1\sigma_r)^2)$ and $fY \sim N(s\mu_r y_1, (sy_1\sigma_r)^2)$. 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 (5) which is reproduced below.

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

Notice that mX, fY and $E[mX - fY | mX + fY > c]$ 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 (5) 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 C.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 C.1, Proposition 3, the substitution for mX and fY remain identical to Equation (4). 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 (6), reproduced below:

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

The random variables, mX and fY, 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., $\sigma_M^2 \neq \sigma_F^2$).*

Proof. As before, we can follow the same argument laid out in Proposition 3, Corollary 3.1 looking at the substitutions for mX and fY, and referring to the expectation in Equation (6) 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.

C.3 Model-Based Simulations: Comparing Tests of $\beta = 1$

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 simulate the model under different functional form assumptions and also allowing for assortative mating. A main conclusion from these simulations is that the statistical tests reported in Foged (2016) regarding the "U-shaped" pattern of household migration are sensitive to functional form assumptions and assumptions about assortative mating. By contrast, the earnings effects of migration (at $s = 0.5$) are consistently robust to these same extensions. We thus conclude that the earnings effects for men and women (at $s = 0.5$) is a robust way to infer how much households discount income earned by the woman compared to the man.

We report simulation results for 3 scenarios:

1. No assortative mating, with men and women drawing base period (pre-move) income independently from gender-specific log-normal income distributions that have equal variance; i.e., men draw from distribution $\log(y_{M1}) \sim N(\mu_M, \sigma_M^2)$ and women drawn from distribution $\log(y_{F1}) \sim N(\mu_F, \sigma_F^2)$, with $\mu_M > \mu_F$ and $\sigma_M = \sigma_F$.

2. Same as above except $\sigma_F > \sigma_M$, which is the case empirically in our data in both countries.

3. Allow for assortative mating, which means that men and women draw from a joint log normal distribution with positive correlation between the base period income draws.

For each scenario, we report results when either all households have $\beta = 1$ or all households have $\beta = 0.8$ (so there are 6 specifications, 3 scenarios $\times$ 2 values of β).

Appendix Table A-9 reports results for these 6 specifications using the quadratic specification in Foged (2016) to test for $\beta = 1$. We report results without any controls in Panel A, and Panel B reports results controlling for 5 household income quintile dummies, as in Foged (2016). The results in column (1) show that whether or not there are income controls, the "U-shape" specification indicates that the female share that minimizes the likelihood of migrating is very close to 0.5, which is exactly what is expected when $\beta = 1$. In both panels, we do not reject that the quadratic minimum is at $s = 0.5$.

Column (2) reports the results from scenario (2.) where men and women draw log income from gender-specific distributions with different variances. Panel A now shows very different results, with the quadratic minimum estimated to be $s = 0.439$ without controls and $s = 0.490$ with controls. In both cases, the statistical test of $s = 0.5$ is rejected at the 5 percent level, even though the true $\beta = 1$. Column (3) shows similar results when accounting for assortative mating, again rejecting $s = 0.5$ in both panels even though the true $\beta = 1$).

The remaining columns show analogous results when $\beta = 0.8$. In Panel B, all results show that the quadratic minimum is estimated to be at a value greater than 0.5, which is what is expected when $\beta < 1$. However, the income controls are required for the test to work properly, because the results in columns (5) and (6) show that even with these controls the test is still not always well-behaved.[51]

Appendix Table A-10 reports results that estimate the average change in earnings for men and women in two subsamples of households: a set of households centered around $s = 0.5$ (i.e., $E[s] = 0.5$ given the set of households chosen to be in the sub-sample), and another set of household centered around $s = 0.4$. Our theoretical results (Propositions 1 and 2) show that whenever $s = 0.5$, the expected change in earnings for couples (conditional on migrating) should be the same for men and women whenever $\beta = 1$ and be larger for men than women whenever $\beta < 1$. The results in Panel A show that this is the case across all columns, whether or not men and women draw log incomes from distributions with equal or unequal variances, and whether or not there is assortative mating.

Taken together, the results in Appendix Tables A-9 and A-10 indicate that testing $\beta = 1$ based on the average change in earnings is reliable, and the results regarding the "U-shape" migration pattern are somewhat sensitive across specifications.

To understand these results intuitively, note that the test in Foged (2016) relies on comparing across a large number of households (to estimate the global minimum of the quadratic function of the female share of household income), which requires comparing households with very different values of s. But this test also requires households to be otherwise very similar. Since households with very different values of s will likely differ in many other dimensions, as well (such as total household income), the most reliable "U-shape" test is likely a semi-parametric estimator that controls very flexibly for all other household characteristics that are correlated with s.

[51]The results show that the statistical test remains well-behaved in the "knife-edge" case where there is no assortative mating and the baseline log normal income distributions for men and women have equal variance. Interestingly, this is the only scenario where baseline household income is also minimized at $s = 0.5$ which intuitively explains why the test remains well-behaved.

By contrast, our empirical approach relies on "zooming in" on households close to $s = 0.5$ and testing whether or not men and women have the same earnings return conditional on moving. This test is not based primarily on comparing *across* households, but rather on comparing men and women *within* a set of households. This explains why the results based on earnings returns are robust to different functional form assumptions and allowing for assortative mating. Intuitively, it does not matter how the households are formed or how baseline income is drawn; as long as one can identify the households close to $s = 0.5$, comparing the earnings returns for men and women is a direct test of $\beta = 1$.

C.4 Model-Based Estimation

This section describes the details of the model-based estimation that recovers an estimate of our primary parameter of interest (β) in each country.

C.4.1 Identification in Simplified Versions of Model

Before describing the estimation procedure, we first discuss identification in some simplified versions of our model to help understand how the full model-based estimation works.

Individual migration benchmark model

First, consider the case of a large number of individuals (not couples) making migration decisions using the same model structure. Individuals start with income y in period 1 and draw a potential return to migration in period 2 from the normal distribution $N(\mu_r, \sigma_r)$. Individuals then choose to move if $\Delta y > c$, with $\Delta y = \mu_r y + \epsilon_r y$ and $\varepsilon_r \sim N(0, \sigma_r)$.

Suppose we have two empirical moments: the average change in income conditional on moving ($\widehat{m}$), and the share of the population moving ($\widehat{p}$). These moments are defined as follows:

$$\begin{aligned}\widehat{m} &= E[\Delta y | \Delta y > c] \\ \widehat{p} &= \Pr(\Delta y > c)\end{aligned}$$

Given the functional form assumptions, we can re-write the two expressions above in terms of standard normal distributions:

$$\begin{aligned}\widehat{m} &= \mu_r y + \sigma_r y \lambda(z) \\ \widehat{p} &= 1 - \Phi(z)\end{aligned}$$

where $z = (c - \mu_r y)/\sigma_r$, and $\lambda(z) = \phi(z)/(1 - \Phi(z))$ is the inverse Mills ratio. With only two moments and three parameters (c, μ_r, σ_r), the parameters not identified. However, if we impose $\mu_r = 0$, then it is straightforward to solve for the remaining parameters in terms of the two moments:

$$\begin{aligned}\widehat{m} &= \sigma_r y \lambda(c/\sigma_r) \\ \widehat{p} &= 1 - \Phi(c/\sigma_r)\end{aligned}$$

$$
\begin{aligned}
&\Rightarrow \\
c &= \sigma_r \Phi^{-1}(1-\widehat{p}) \\
\sigma_r &= \frac{\widehat{m}}{y\lambda(\Phi^{-1}(1-\widehat{p}))}
\end{aligned}
$$

Since the right-hand expressions for c and σ_r are strictly monotonic they will generally have a unique solution given the empirical moments and known income y.

The expressions for the two model parameters have intuitive comparative statics. For example, holding constant σ_r, a lower estimated migration probability leads to higher estimated migration cost parameter. Additionally, holding constant the migration probability, a higher average earnings return leads to a higher estimated variance in the returns to moving.

Household migration benchmark model

Now we return to the baseline model of households making migration decisions, and we impose $\beta = 1$. In each couple, the man starts with income y_M and the woman starts with income y_F (with $y_M > y_F$). Both members of the couple independently draw potential returns to migration in period 2 from the same normal distribution $N(\mu_r, \sigma_r)$. The household then chooses to move if $\Delta y_M + \Delta y_F > c$, with $\Delta y_i = \mu_r y_i + \varepsilon_r y_i$, where $\varepsilon_r \sim N(0, \sigma_r)$.

Now suppose we have three moments, the average change in income conditional on moving for men and women ($\widehat{m_M}$ and $\widehat{m_F}$), and the share of the population moving ($\hat{p}$). These moments are defined as follows:

$$
\begin{aligned}
\widehat{m_M} &= E[\Delta y_M | \Delta y_M + \Delta y_F > c] \\
\widehat{m_F} &= E[\Delta y_F | \Delta y_M + \Delta y_F > c] \\
\widehat{p} &= \Pr(\mu_r y + \epsilon_r y > c)
\end{aligned}
$$

As above, given the function form assumptions we can re-write the expressions in terms of standard normal distributions, using the fact that the returns to migration are drawn independently within the couple. This leads to the following expressions:

$$
\begin{aligned}
\widehat{m_M} &= \mu_r y_M + \sigma_r y_M \frac{y_M}{\sqrt{y_M^2 + y_F^2}} \lambda(z) \\
\widehat{m_F} &= \mu_r y_F + \sigma_r y_F \frac{y_F}{\sqrt{y_M^2 + y_F^2}} \lambda(z) \\
\widehat{p} &= 1 - \Phi(z)
\end{aligned}
$$

where $z = (c - \mu_r y_M - \mu_r y_F)/\sqrt{(\sigma_r y_M)^2 + (\sigma_r y_F)^2}$ and $\lambda(z)$ is the inverse Mills ratio defined above. Unlike in the individual migration model, we now have 3 moments and 3 model parameters, and by re-arranging the expressions above we can solve for closed-form formulas of each model parameter in terms of the empirical moments and known parameters. To do this, begin by noting that the last expression implies that $z = \Phi^{-1}(1-\widehat{p})$;

we then can substitute this into the expressions for $\widehat{m_M}$ and $\widehat{m_F}$:

$$\widehat{m_M} = \mu_r y_M + \sigma_r y_M \frac{y_M}{\sqrt{y_M^2 + y_F^2}} \lambda(\Phi^{-1}(1 - \widehat{p}))$$
$$\widehat{m_F} = \mu_r y_F + \sigma_r y_F \frac{y_F}{\sqrt{y_M^2 + y_F^2}} \lambda(\Phi^{-1}(1 - \widehat{p}))$$

We next re-write the two expressions above in matrix form as follows:

$$\begin{pmatrix} \widehat{m_M}/y_M \\ \widehat{m_F}/y_F \end{pmatrix} = \begin{pmatrix} 1 & y_M A \\ 1 & y_F A \end{pmatrix} \begin{pmatrix} \mu_r \\ \sigma_r \end{pmatrix}$$

where $A = \frac{1}{\sqrt{y_M^2 + y_F^2}} \lambda(\Phi^{-1}(1 - \widehat{p}))$, which is in terms of empirical moment $\widehat{p}$ and known income values y_M and y_F. Inverting the matrix above, we can solve for parameters μ_r and σ_r:

$$\begin{pmatrix} \mu_r \\ \sigma_r \end{pmatrix} = \begin{pmatrix} 1 & y_M A \\ 1 & y_F A \end{pmatrix}^{-1} \begin{pmatrix} \widehat{m_M}/y_M \\ \widehat{m_F}/y_F \end{pmatrix}$$
$$\begin{pmatrix} \mu_r \\ \sigma_r \end{pmatrix} = \frac{1}{y_F A - y_M A} \begin{pmatrix} y_F A & -y_M A \\ -1 & 1 \end{pmatrix} \begin{pmatrix} \widehat{m_M}/y_M \\ \widehat{m_F}/y_F \end{pmatrix}$$
$$\Rightarrow$$
$$\mu_r = \frac{\widehat{m_F}/y_F * (y_M/y_F) - \widehat{m_M}/y_M}{y_M/y_F - 1}$$
$$\sigma_r = \frac{\widehat{m_M}/y_M - \widehat{m_F}/y_F}{y_M A - y_F A}$$

Since $y_M > y_F$, the denominator in the expressions for μ_r and σ_r is strictly positive. The expression for σ_r implies that the percentage increase in earnings for men will always be larger than the percentage increase for women, and the larger the percentage gap, the larger the estimate of σ_r (holding constant the baseline incomes and the value A). The expression also shows how μ_r and σ_r are separately identified. The larger earnings return (normalized by baseline income) for men compared to women pins down σ_r, but if it is proportionally larger by exactly the baseline gender earnings gap (i.e., if $\widehat{m_M}/y_M$ divided by $\widehat{m_F}/y_F$ is equal to the baseline gender gap y_M/y_F), then $\mu_r = 0$. This shows how the relative magnitude of the earnings return for men and women jointly pin down μ_r and σ_r in our model under independence. Given μ_r and σ_r, then c is immediately given by $\widehat{p} = 1 - \Phi(z)$.

All of the previous results for the individual migration model and the household migration model are presented assuming a given income (y, or y_M and y_F). With baseline heterogeneity in income, the identification arguments can proceed analogously by integrating over the baseline distribution of income for men and women in each household. This is exactly the procedure that we follow in the model-based estimation, which we now describe in the remainder of this section.

C.4.2 Simulated method of moments algorithm

We simulate 100,000 households, each with a male ($i = M$) and a female ($i = F$). We draw baseline income in period 1 from the gender-specific log-normal income distribution $\log(y_{i1}) \sim N(\mu_i, \sigma^2)$, and we calibrate the two parameters so that the average income for men and women matches the mean and standard deviation of income for each gender in the movers sample in the year prior to the move (as reported in Table 1); this leads to baseline income distribution parameters reported in Panel A of Table 4. This initial simulation also generates a simulated distribution of $\hat{s}$ based on the baseline income distribution, and we can then divide the simulated households into three groups based on simulated $\hat{s}$ to match the three groups reported in the reduced-form analysis. We can the simulate the average earnings return to moving (conditional on moving) in each of these groups and compare these simulated results to the the reduced-form empirical estimates.

In each iteration of the simulation, we choose values for the 4 remaining unknown parameters (μ_r, σ_r, c, and β) and we then simulate the model in period 2 and calculate the average change in earnings for each of the three sub-groups of households (defined based on $\hat{s}$). We define the parameter vector $\boldsymbol{\theta} = (\mu_r, \sigma_r, c, \beta)$. Given a set of values of the 4 model parameters in $\boldsymbol{\theta}$, we draw potential earnings for the male and female in each household in period 2, and the household chooses to move if $\Delta y_M + \beta \Delta y_F > c$.

As described in the main text, the 4 model parameters are estimated using 5 moments: the average earnings return for men and women in the $\hat{s} > 0.5$ sub-group (2 moments), the average earnings return for men and women in the $s^* \leq \hat{s} < 0.5$ sub-group (2 moments), and the overall migration rate in the full sample. We use $\hat{\boldsymbol{\pi}}$ to indicate the vector of the reduced-form empirical moments (reported in Table 3), and we use $\boldsymbol{\pi}(\boldsymbol{\theta})$ to indicate the vector of the analogous simulated moments at the parameter vector $\boldsymbol{\theta}$.

We repeat the simulation above a large number of times and search for the combination of model parameters that minimizes the following weighted minimum-distance criterion:

$$m = (\hat{\boldsymbol{\pi}} - \boldsymbol{\pi}(\boldsymbol{\theta}))'\hat{(W)}^{-1}(\hat{\boldsymbol{\pi}} - \boldsymbol{\pi}(\boldsymbol{\theta})),$$

where $\hat{W}^{-1}$ is the inverse of the estimated sampling variances for each of the reduced-form empirical estimates.[52] We define $\hat{\boldsymbol{\theta}}$ to be the parameter vector that minimizes m.[53]

C.4.3 Standard errors

We calculate standard errors for the model parameters using the following variance-covariance matrix:

$$V = (\hat{G}'\hat{(W)}^{-1}\hat{G})^{-1},$$

[52] We use the regression-based standard errors for the 4 earnings moments, and we calculate the standard error of the migration rate estimate ($\hat{m}$) as $\sqrt{(}\hat{m}(1-\hat{m})/N)$ where N is the size of the population sample used to calculate the migration rate.

[53] We do not have a formal proof that this parameter vector is unique, but given the description and behavior of the two-step iterate algorithm described in the main text, we strongly suspect that there is a unique minimum in non-degenerate cases.

where $\hat{G} = \partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}})/\partial \hat{\boldsymbol{\theta}}$. We calculate $\hat{G}$ numerically using perturbations around the optimal $\hat{\boldsymbol{\theta}}$ estimate.

C.4.4 Goodness-of-fit test statistic

Since we use 5 moments to estimate 4 parameters, we can calculate a goodness-of-fit test statistic $(\hat{\boldsymbol{\pi}} - \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}))'\hat{(}W)^{-1}(\hat{\boldsymbol{\pi}} - \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}))$, which is distributed as $\chi^2(5-4) = \chi^2(1)$. When we impose $\beta = 1$ and re-estimate the model parameters, we can calculate the same test statistic (now distributed as $\chi^2(2)$), and we report p-values of the over-identification test.

C.5 Extended Model of the Child Penalty

In this section we present a 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, η_M and η_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 the man and the woman in the household.

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

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

subject to the same budget constraint ($c \leq w_M h_M^C + w_F h_F^C$), with $\theta = (1/(1-\kappa) * (T - h_M^C + T - h_F^C)^{(1-\kappa)}$. Following Andresen and Nix (2022) , the θ parameter is interpreted as the benefit of the household members from spending time with the child, and λ governs the utility to the household of this time investment.

In this setup, the change in income after having a child is defined as the "child penalty" and is given by $(w_i h_i^C - w_i h_i)/(w_i h_i)$ for $i = M, F$. In the simulations reported in the main text, we extend this model by 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.[54]

[54] This is mathematically equivalent to assuming that marginal utility is linear in each household member's income, and the marginal utility of the female income is β times the marginal utility of male income.

To calibrate the model, we choose the baseline gender wage gap to be $w_F/w_M = 0.79$ in Sweden and $w_F/w_M = 0.85$ in Germany. We choose $\gamma = 1.5$, $\eta_M = \eta_F = 1.0$, and $\kappa = 0.75$. The γ parameter is related to the inverse of the uncompensated labor supply elasticity, so we choose a value above one so that labor supply is not too elastic to the wage. We choose $\kappa = 0.75$ so that the average decline in income when $\beta = 1$ and $w_F/w_M = 1$ is 9% for both members of the household. This is very close to the estimates for same-sex couples studied in Andresen and Nix (2022). Lastly, we choose $\eta_M = \eta_F = 1.0$ so that labor supply is more elastic to wage after children relative to before. Note that both elasticity parameters are assumed to be the same by gender because we want to transparently isolate the quantitative importance of $\beta < 1$ in accounting for the child penalty without allowing for any other gender differences in preferences.

Using these parameters, we then simulate the model for $\lambda = 0$ (no child) and $\lambda = 1.5$ (child) at the two different values of β and report the change in earnings for men and women in Table 6 in the main text. What the simulation exercise shows is that with no gender differences in preferences for spending time in child-rearing and a realistic gender wage gap and 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, so the household would optimally choose for the woman to work much less (compared to the man) after their first child arrives.