Preliminary and incomplete

Moving to Opportunity, Together*

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February 10, 2024

Abstract

Many couples face a trade-off between advancing one spouse's career or the other's. We study this trade-off by analyzing the earnings effects of relocation and the effects of a job layoff on the likelihood of relocating using detailed administrative data from Germany and Sweden. Using an event-study analysis of couples moving across commuting zones, we find that relocation increases men's earnings more than women's, with strikingly similar patterns in Germany and Sweden. Using a sample of mass layoff events, we find that couples in both countries are more likely to relocate in response to the man being laid off compared to the woman. We then investigate whether these gendered patterns reflect men's higher earnings or a gender norm that prioritizes men's career advancement. To do this, we develop a model of household decision-making in which households place more weight on the income earned by the man compared to the woman, and we test the model using the subset of couples where the man and woman have similar potential earnings. For both countries, we show that the estimated model can accurately reproduce the reduced-form results, including those not used to estimate the model. The results point to a role for gender norms in explaining the gender gap in the returns to joint moves.

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 Eva Forslund, Daisy Lu, Angelo Marino, Isaac Norwich, 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 (RDC-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

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

Early models of the household posited that couples will make location decisions to maximize joint income (Mincer 1978; Frank 1978). Joint location decisions could therefore exacerbate the gender earnings gap if men have higher earnings or earnings potential than women. In such cases, couples may choose locations that benefit the man's career while the woman becomes the "trailing spouse", working in a job that does not match her skills or pays less than the job she would have if she were maximizing only her own earnings. However, numerous studies have shown that gender norms also influence household and individual decision-making (see, for example, Bertrand et al. 2015; Boelmann et al. 2021; Bursztyn et al. 2017). If couples adhere to traditional gender norms, location decisions may systematically be made to benefit the man's career beyond what can be explained by his higher earnings potential.

In this paper, we use administrative data from Germany and Sweden to study the impact of moving on men's and women's earnings and to test how much of the gender earnings gap from moving is due to differential earnings potential versus gender norms. 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 11% and 5% in Germany and Sweden over the first five years following the move, women experience small changes in their earnings of 3% and -1%, respectively. These differences persist over the first 10 years post-move. The earnings gap arises through

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

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

We also employ an additional research design to test whether moves disproportionately help men or women within a couple: we use mass layoff events to test whether couples are more likely to move when the man is laid off as opposed to the woman. Mass layoffs generate plausibly exogenous job separations for both men and women in our sample and induce long-distance moves (Huttunen et al. 2018). In Germany, we find that the likelihood of moving increases following the layoff of either a man or a woman, but couples are nearly twice as likely to move when a man is laid off compared to when a woman is laid off. In Sweden, the likelihood that a couple moves doubles when the man is laid off, but does not change significantly when the woman is laid off. These results may help explain why women suffer larger earnings losses following a layoff relative to men: they are less able to take advantage of job opportunities in other localities (Illing et al. 2023).

To distinguish between different potential explanations for these reduced-form results, we develop a model of household decision-making in which households potentially 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 in a standard collective model of joint income maximization (net of migration costs) — 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 be reversed when the woman is the primary breadwinner. We find in both countries that the earnings gap that emerges following a move is indeed smaller among couples in which the woman has a higher predicted share of household income, consistent with potential earnings differences explaining some of the overall gender gap in the earnings effects of relocation. 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. A standard collective model would predict that women benefit more than men from moving among these couples, and we do not see this. In Sweden, the gender gap closes but does not reverse, while in Germany, men continue to benefit more than women following a move even when the woman has higher potential earnings.

With these empirical results as motivation, we estimate the model parameters separately for each country using simulated method of moments. We test and reject a collective model of decision-making in both countries, with larger deviations from the collective benchmark in Germany than in Sweden. We also show that the model can reproduce the gender differences in the effects of a job layoff on the probability of moving, even though these results were not directly targeted in the model estimation.

Our reduced-form results use a relatively standard event-study framework as well as mass layoff events to generate exogenous job separations. For both research designs, we present visual evidence that the identification assumptions are plausible in both countries. When we interpret our model estimates as evidence of a gender norm of prioritizing men's careers, with couples choosing to leave money on the table, this requires stronger assumptions. We are assuming that men and women have the same job opportunities and expected returns to migration, conditional on predicted earnings. One way this might be violated is if women tend to be in occupations with lower returns to moving, but we find similar results when we re-weight the sample so that the occupational distribution is the same for men and women.[2]

Another alternative explanation is that couples are rationally anticipating that the woman will soon leave the labor market, for example, after the birth of a child. Therefore, even if a woman currently has higher earnings potential than a man, the couple may anticipate her earnings being substantially lower in the future. To investigate this possibility, we compare the earnings gap between couples who do not have a child in our sample period and those who do, finding that the gap is only slightly smaller among couples that do not have a child.

[2]We can only do this exercise for Germany, as the Swedish data do not include occupation. In general, we leverage the strengths of each data set in our robustness checks. For example, we can test if moves are to be closer to grandparents or to reduce women's commuting distance in the Swedish data but not the German data.

We also implement a direct test of gender norms by comparing couples who are of East or West German origin. Prior work has shown that women with East German origins are more likely to work and also return to work more quickly following the birth of a child (Rosenfeld et al. 2004; Boelmann et al. 2021). Studies have also shown that men's childhood exposure to working women influences their wives' labor supply (Fernandez et al. 2004). Consistent with this literature, 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 completely absent among couples in which the man grew up in East Germany.

This test also helps rule out another alternative explanation for the main results, which is that employers discriminate against women when making job offers to candidates who would need to relocate (perhaps anticipating that women would be less able to do so). In our comparison of couples with and without East German origins, labor market discrimination and other demand-side factors are held fixed, so they are not the explanation for the more gender-equal effects of moves among couples with East German origins.

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

Our paper relates to a large literature on the source of gender gaps in labor market outcomes. A number of papers have found that child penalties play an important role in the 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 show a lower willingness to commute (Le Barbanchon et al. 2020). In addition, social norms or psychological attributes such as willingness to compete, risk preferences, and self-confidence may directly affect job search and wages (e.g., Bertrand et al. 2015; Buser et al. 2014; Cortes et al. 2021; Wiswall and Zafar 2017). A further potential explanation, which is the focus of this paper, is that married women may take less advantage of career-enhancing long-distance moves or may even experience earnings losses as a tied mover.

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

Our paper also relates to more recent research examining the implications of location decisions on gender inequality. Fadlon et al. (2022) examine male and female medical graduates' internship choices in Denmark. The authors find that women choose internships in lower-quality labor markets than men, and this explains a large fraction of subsequent gender inequality among physicians in human capital accumulation and wages. Venator (2020) uses the NLSY97 to test how unemployment insurance generosity affects couples' migration decisions, finding that access to UI increases migration rates and women's post-move earnings. Relative to this work, we develop and test a model-based explanation that allows for a gender norm that prioritizes the man's career within the couple.

The remainder of the paper proceeds as follows. We describe the two administrative datasets as well as our sample and variable construction in section 2. Section 3 describes our empirical strategy, and we present the reduced-form results in section 4. Section 5 provides a direct test that gender norms play a role in explaining the results. Section 6 develops a model of household decision-making, presents additional empirical results motivated by the model, and quantifies the role of gender norms in explaining our empirical results. In Section 7 we explore alternative mechanisms. Section 8 concludes.

2 Data

We use administrative data from Sweden and Germany to test whether, within heterosexual couples, moves disproportionately benefit men. These datasets have several valuable 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. Second, the data include detailed labor market histories of both spouses, allowing us to precisely account for spouses' pre-move employment outcomes and study the post-move dynamics. Third, we can identify mass layoff events at the establishment level, which we can use as an exogenous negative labor market shock that could lead to a move. Finally, the data allow for much larger samples than longitudinal surveys.

2.1 German Data

For Germany, we use a 25% random sample of married couples that can be identified in the administrative data base Integrated Employment Biographies (IEB) with the couple identifier generated by Baechmann et al. (2021).[3] 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

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

al. (2017): for two people to be matched as a couple, the spouses must live in the same location (geocoded building), have a matching last name (at least one part in case of double names), 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.[4]

The algorithm produces few false positives, and much more important are married couples who not identified: only about one third of married couples living in Germany and attached to the labor market are found (Goldschmidt et al. 2017). The main reason is that for a large number of individuals in the IEB, no exact building geocodes are assigned (Baechmann et al. 2021). In addition, the algorithm identifies fewer couples living in large buildings, and it misses out on those with no common surname, who are likely to be less conservative on average. That said, sharing a common name is still widespread: for couples who married in 1996 (2016), 91% (87%) share a common name (GFDS 2018). 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. The earnings information is very accurate, as the employer has to report earnings for social security purposes. However, the data reports wages only up to the social security contribution ceiling, so we impute right-censored wages.[5] In addition, the IEB 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 like year of birth and education. The data providing institute can link employment spells to establishments and, from these links, variables indicating mass layoffs have been created.[6]

[4]The identification of couples is done every year on June 30 from 2001 to 2014, which implies that in a particular year, two people are only identified as a couple if both spouses have a record in the IEB on June 30.

[5]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).

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

We restrict the data to couples in which at least one was between age 25 and 45 at the time of the move (or layoff).

2.2 Swedish Data

We use individual-level administrative data from Sweden from the GEO-Sweden database, covering 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 coordinates.

Couples share a joint family ID if they are married or have a joint child, but through origin and destination residential building IDs we can additionally identify joint moves of cohabiting couples regardless of their marital or parental status. We follow the Statistics Sweden definition of a cohabiting couple: two individuals of opposite sexes who are no more than 15 years apart in age, are not related, and are the only two individuals residing in the same building who meet the other criteria to be matched together.As in the German data, we exclude couples in which either spouse is 25 to 45 years old at the time of the move or layoff.

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 predicting an individual's income, 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.

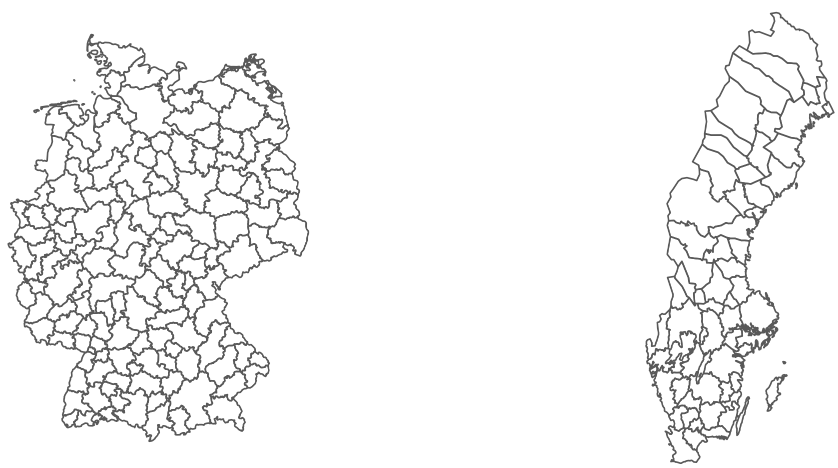
The Swedish data link parents and children, so we observe the year of birth for all of an individual's children.

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

Figure 1: Maps of Commuting Zones

(a) Germany (b) Sweden



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

2.4 Sample and Variable Definition and Descriptive Statistics

2.4.1 Movers Sample

In our analysis, we consider joint moves of couples occurring between 1995-2007 in Sweden and 2001-2011 in Germany. During the observation period, a few couples experienced multiple long-distance moves. We consider only their first move, because future outcomes may be influenced by the first move.

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

As discussed above, we impose the restriction that at least one member of the couple is age 25 to 45 at the time of the move. In addition, we attempt to exclude couples in which at least one person is a student just prior to the move (so that income changes following the move are not due to initial entry into the labor market). In the Swedish data, we use the receipt of student benefits to identify student status. If either member of the couple is a student in the move year or either of the two years prior to the move, we exclude the couple from the sample.[8] In the German data, we use enrollment in firm-based education (e.g., apprentice, intern) as our proxy for student status; we do not have information on college enrollment. Finally, couple-years in which one spouse is above 60 or below 16 years old are excluded.

We construct a panel that includes all couples 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). Our final sample consists of $22,556$ moving couples in Germany and $44,499$ couples in Sweden.

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%.[9] 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 consists 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).[10]

[8]In addition, for couples who are retained, we drop couple-years before the move (earlier than $t = -2$) when one or both of them is a student.

[9]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.

[10]Further restrictions are (1) the pair is identified as a couple before the layoff, (2) the worker does not return to the establishment in the five subsequent years, (3) both partners are not laid off at the same time, and (4) it is the person's first layoff we observe.

Note that for Sweden, we cannot include cohabiting couples without children in the layoff analysis, as we can only identify couples through their family ID. Here we are not restricting the sample to couples who move, so we cannot use origin and destination building IDs to identify cohabiting couples without children like we do for the movers analysis.

2.4.3 Variable Definitions and Descriptive Statistics

The main outcome variable that we consider in our analysis is gross yearly wage income (in 2017 euros) of each spouse. Information on hours worked is not available. For non-working spouses, the wage income is set to zero.

Table 1 presents descriptive statistics for the German and Swedish mover samples. The average age of couples is similar in both samples, with men being slightly older than women. Education levels differ across the two countries, consistent with their different education systems. Several baseline gender gaps emerge. 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.[11] 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 a couple has a child.

Table 2 presents descriptive statistics for the layoffs sample. The columns labelled "Layoff Men" 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, but we still see a gender gap in earnings. The fraction of couples with at least one child is especially high in Sweden since cohabitating couples are identified and included in the sample based on the presence of a child.

Because of differences in the sample characteristics for male layoffs versus female layoffs, we include a non-layoff comparison group in our analysis. This allows us to net out the observed differences when comparing the effects of male and female layoffs on household moves.

[11] Among 25 to 54 year-olds in 2010, the share of part-time workers for men and women were 5.6 and 39.1% in Germany, and 5.0 and 13.4% in Sweden, according to the OECD (https://stats.oecd.org/).

Table 1: Summary Statistics for Movers Sample

	Germany		Sweden	
	Men (1)	Women (2)	Men (3)	Women (4)
Age	36.16	33.87	35.00	32.71
	(6.17)	(6.12)	(6.86)	(6.33)
Compulsory schooling	0.01	0.03	0.13	0.12
	(0.11)	(0.17)	(0.33)	(0.33)
High school	0.05	0.06	0.48	0.44
	(0.21)	(0.25)	(0.50)	(0.50)
Vocational training	0.60	0.68	0.07	0.04
	(0.49)	(0.46)	(0.26)	(0.20)
Some college			0.07	0.12
			(0.26)	(0.32)
College	0.34	0.22	0.25	0.28
	(0.47)	(0.42)	(0.43)	(0.45)
Potential experience	17.17	15.17	15.32	13.03
	(6.43)	(6.32)	(0.43)	(0.45)
Wage income (1000s EUR)	44.11	19.79	28.94	16.60
	(39.95)	(22.04)	(19.48)	(14.05)
Employed	0.88	0.78	0.89	0.84
	(0.33)	(0.41)	(0.31)	(0.36)
Unemp. benefits (1000s EUR)	0.61	0.39	0.90	0.99
	(2.06)	(1.40)	(2.72)	(2.59)
Days receiving UI benefits (per year)	20.80	20.92	23.94	24.51
	(66.30)	(70.20)	(64.71)	(62.95)
At least 1 child	0.62	0.62	0.66	0.66
	(0.49)	(0.49)	(0.47)	(0.47)
Non-native	0.08	0.08	0.13	0.14
	(0.27)	(0.28)	(0.34)	(0.35)
Observations	20566	20566	44499	44499

Notes: This table displays means and standard deviations (in parentheses) for different outcomes in the period before the move ($t-1$) in Germany and Sweden for the movers sample. In the German data we measure completed college instead of some college.

Table 2: Summary Statistics for Job Layoffs Sample

	Germany				Sweden			
	Layoff Men		Layoff Women		Layoff Men		Layoff Women	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
Age	38.26	36.51	40.77	38.24	37.49	35.90	40.01	37.40
	(4.85)	(5.65)	(5.93)	(5.03)	(4.95)	(5.63)	(6.20)	(5.05)
Compulsory schooling	0.01	0.02	0.01	0.01	0.11	0.08	0.15	0.09
	(0.09)	(0.15)	(0.08)	(0.10)	(0.31)	(0.28)	(0.36)	(0.29)
High school	0.09	0.09	0.06	0.09	0.55	0.53	0.54	0.55
	(0.28)	(0.28)	(0.23)	(0.29)	(0.50)	(0.50)	(0.50)	(0.50)
Vocational training	0.76	0.79	0.78	0.79	0.12	0.03	0.06	0.04
	(0.43)	(0.41)	(0.41)	(0.41)	(0.32)	(0.18)	(0.24)	(0.20)
Some college					0.06	0.15	0.06	0.11
					(0.23)	(0.36)	(0.25)	(0.31)
College	0.14	0.10	0.15	0.11	0.17	0.20	0.19	0.21
	(0.35)	(0.30)	(0.36)	(0.31)	(0.37)	(0.40)	(0.39)	(0.41)
Potential experience	19.76	18.07	22.03	19.69	17.08	15.49	19.86	17.13
	(5.07)	(5.85)	(6.13)	(5.29)	(5.32)	(5.88)	(6.73)	(5.53)
Wage income (1000s EUR)	43.87	16.95	41.14	28.17	38.21	17.39	32.71	25.43
	(27.14)	(17.11)	(30.97)	(15.63)	(16.08)	(13.47)	(19.12)	(12.16)
Employed	1.00	0.85	0.93	1.00	1.00	0.90	0.93	1.00
	(0.00)	(0.36)	(0.25)	(0.00)	(0.00)	(0.30)	(0.25)	(0.00)
Unemp. benefits (1000s EUR)	0.60	0.30	0.43	0.45	0.44	0.73	0.54	0.47
	(1.61)	(1.19)	(1.70)	(1.21)	(1.72)	(2.16)	(2.16)	(1.64)
Days receiving UI benefits (per year)	16.47	18.60	16.16	18.77	11.49	15.32	11.88	9.86
	(41.26)	(70.34)	(59.97)	(46.28)	(39.25)	(48.20)	(46.87)	(35.75)
At least 1 child	0.57	0.57	0.47	0.47	0.91	0.92	0.89	0.90
	(0.49)	(0.49)	(0.50)	(0.50)	(0.28)	(0.28)	(0.31)	(0.31)
Non-native	0.08	0.07	0.05	0.05	0.10	0.11	0.10	0.09
	(0.28)	(0.26)	(0.23)	(0.22)	(0.30)	(0.31)	(0.30)	(0.29)
Observations	6828	6828	4458	4458	8052	8052	6768	6768

Notes: This table displays means and standard deviations (in parentheses) for different outcomes in the period before the layoff ($t-1$) in Germany and Sweden for the job layoffs sample. In the German data we measure completed college instead of some college.

3 Empirical Strategy

3.1 Event-study analysis of the effects of moves

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

One threat to our strategy is that might couples move when women (or men) are choosing to exit or enter the labor market, or to work less. For example, if couples choose to move when they are starting a family, the move will coincide with women temporarily leaving the labor market. We therefore also control for child event-time indicators.

Our main estimation equation is:

$$\begin{aligned} Y^g_{ist} = \sum_{j \neq -1} \alpha^g_j \times \mathbb{1}[j = t] + \sum_p \sum_k \beta^g_{pk} \times \mathbb{1}[p = educ_{is}] \times \mathbb{1}[k = e\hat{x}p_{is}] \\ + \sum_y \nu^g_y \times \mathbb{1}[s = y] + \sum_m \tau^g_m \times \mathbb{1}[m = t_{ch}] + \theta^g NoChild_{ist} + \epsilon^g_{ist} \end{aligned} \quad (1)$$

where the outcome of interest is individual i's wage income in year s and event time t. The first term consists of event-time indicators, which we estimate for five years before and ten years after a move. We estimate equation 1 separately by gender g and include controls for potential experience ($e\hat{x}p$), education level ($educ$), and their interaction, as well as calendar year indicators ($y = s$), child event-time indicators ($m = t_{ch}$), and an indicator for having no children, $NoChild_{ist}$.[12] Standard errors are clustered at the individual level.

This design does not account for the fact that 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 7 by re-weighting men and women to have the same occupational distribution, among other robustness checks.

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 zero in on laid off individuals (e.g., having a tenure of at least one year) create some 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 assign a 'placebo layoff' date to the control group, following Kleven et al. (2019a).[13]

We then estimate the following equation:

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

[12]For Sweden, there are five education levels: compulsory schooling, high school, vocational training, some college, and college. For Germany, there are three: high school or below, vocational training, and some college.

[13]We assign a "placebo" age at layoff based on the actual gender-specific age distributions within the displaced workers cohort-education cell.

where M_i is a dummy indicating whether couple i lives in a different CZ 1 year after the layoff, and X_i is a vector of controls (age of both spouses at layoff).

4 Results

4.1 Descriptive Results on the Effects of Moving

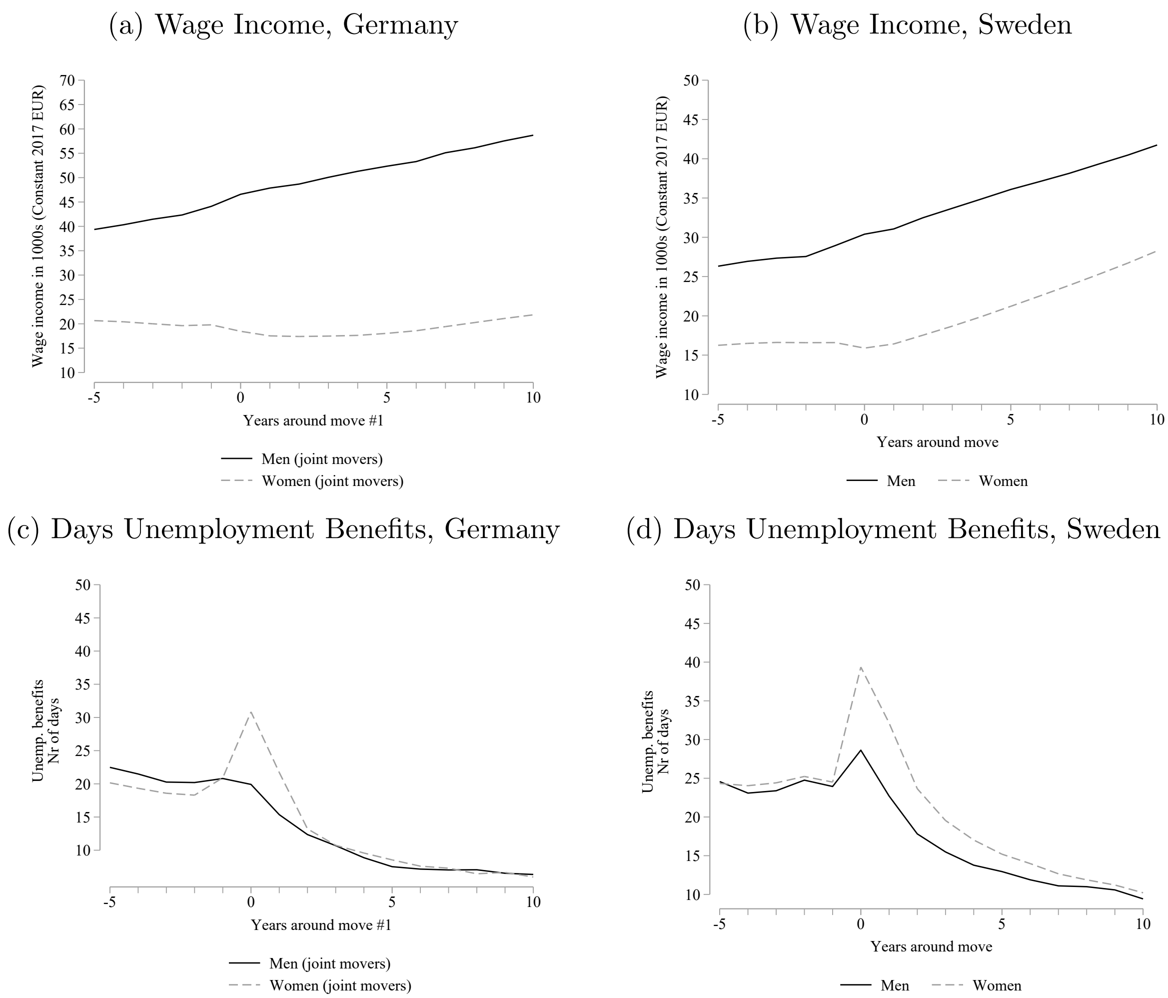
We begin by separately plotting men's and women's unconditional wage income and employment status following a move, shown in Figure 2. Panels (a) and (b) show the wage income for German and Swedish couples who move together for the first time. Both men's and women's incomes are relatively flat prior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

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

4.2 Main Results: Earnings Effects of Moving

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

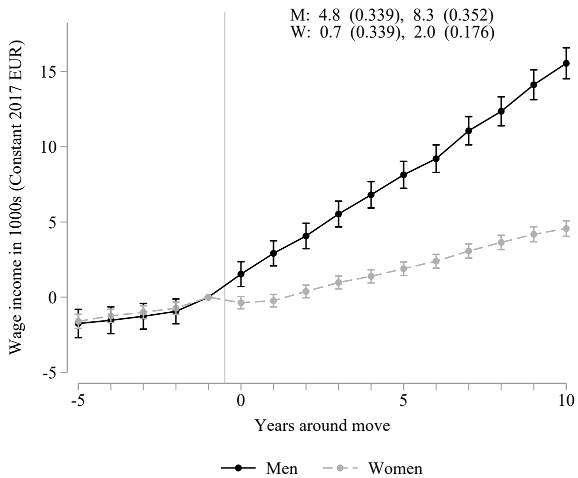
Figure 2: Relationship between Moving and Labor Earnings and Employment



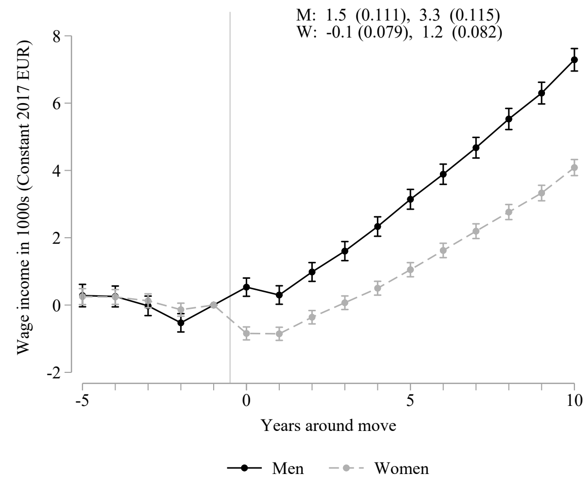
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first move, per gender.

Figure 3: Impact of Move on Labor Earnings and Employment

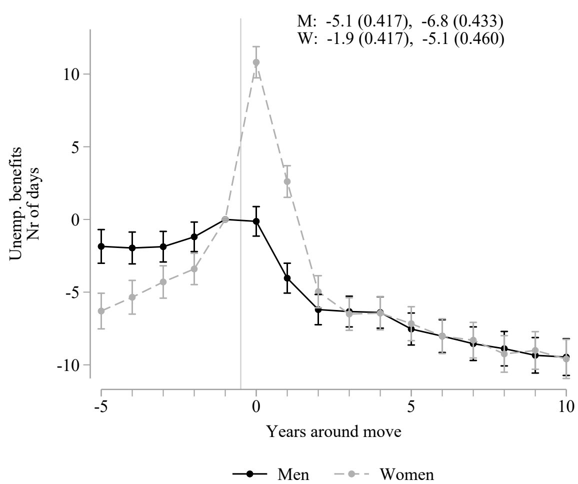
(a) Wage Income, Germany



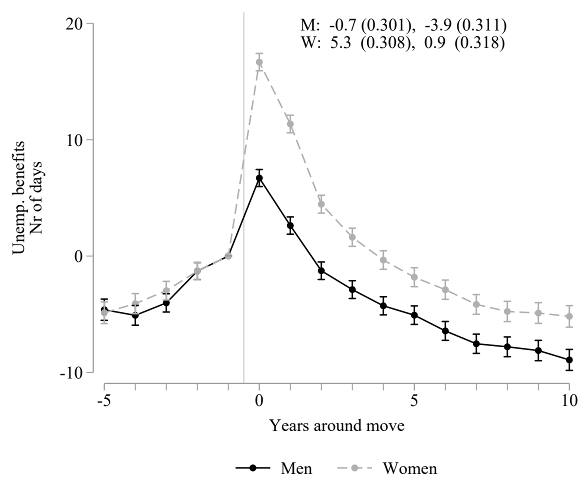
(b) Wage Income, Sweden



(c) Days Unemployment Benefits, Germany



(d) Days Unemployment Benefits, Sweden

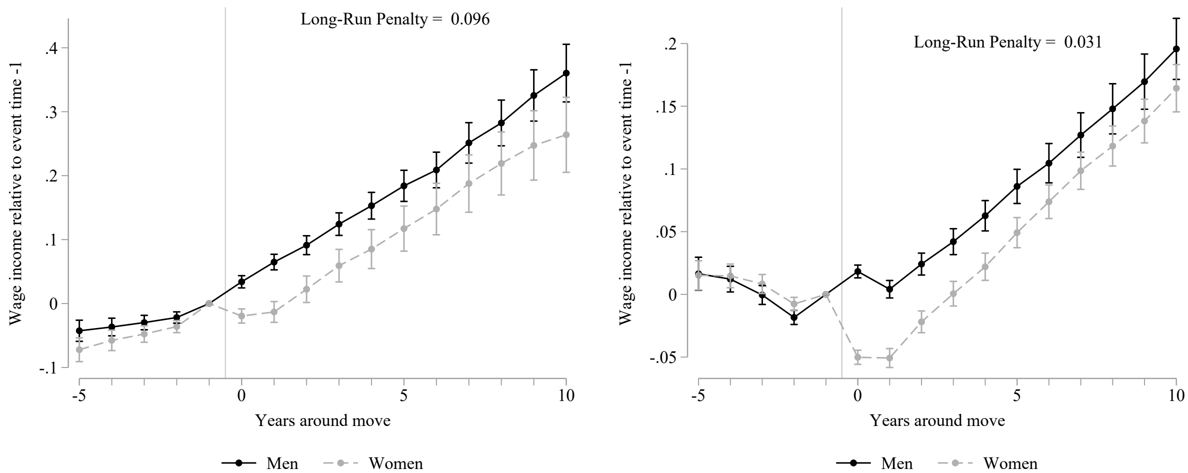


Notes: This figure displays the event study results that estimate the effect of moving on different outcomes in each year relative to the year before the move ($t - 1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level.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

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

Figure 4: Proportional Impact of Move on Wage Income

(a) Germany (b) Sweden



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

To investigate whether spouses' earnings responses are driven by changes in employment or in wages, panels (c) and (d) of Figure 3 and (a)-(f) of Figure OA-1 show the effects of a move on various employment measures. In Germany, the annual number of days employed increases by 20 days in the year immediately following a move for men and by less than 10 days for women. However, employed days continue to increase over time and eventually converge. We also see a spike in the annual number of days the individual collects unemployment benefits following a move that is much more pronounced for women than for men (17 days versus 7 days). These results suggest that at least part of the divergence in men's and women's earnings is due to women leaving employment for a period of time following a move.

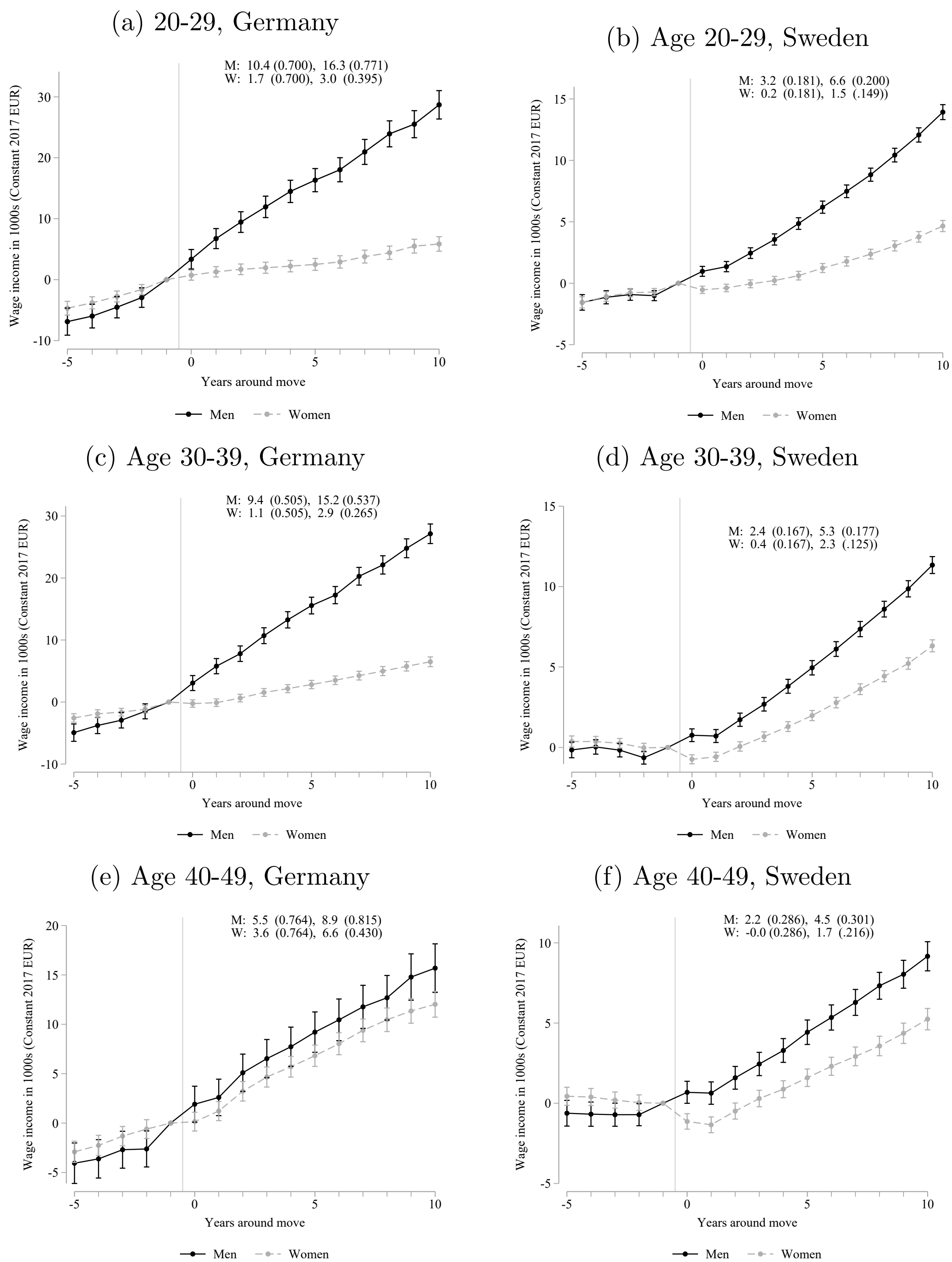
The results in Figure 3 indicate that relocation increases wage earnings of men more than women in absolute terms, and Figure 4 indicates that this is true in proportional terms, as well. Figure 4 normalizes the event study estimates in Figure 3 (panels (a) and (b)) by the average income of men and women in each country in the year prior to the move).[14] These results show that moving increases the average earnings growth for men by a greater percentage than women; specifically, 10 years after the move, men experience a 9.6 percentage point higher earnings growth compared to women in Germany, and in Sweden the gender gap is 4.3 percentage points. Interestingly, in both countries men and women each experience long-run increases in earnings, even while men experience greater earnings growth in both absolute and percentage terms. The fact that average earnings increase significantly for both members of the household is consistent with non-negligible migration costs.[15]

Previous research showed that young individuals are more likely to move (Polachek and Horvath 2012) and that the returns to moving are larger for younger individuals (Bartel 1979). To test whether the treatment effects vary with age, we define age groups (20–29, 30–39, and 40–50) based on the average age of the spouses in pre-move year $t-1$. The results, displayed in Figure 5, show that the wage-income returns to moving decline with age for both spouses. 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.

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

[15]We do not find that moves are systematically to higher-income areas, as shown in Figure OA-2, which conducts the event study analysis with the estimated commuting-zone earnings fixed effect as the outcome.

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



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

4.3 Mass Layoff Results

The previous results show the emergence of a significant earnings gap following a joint move, with men enjoying more earnings growth following a move than women. In this section, we present a second test of whether moves are prompted more by men's career needs than women's. We use mass layoff events to test whether couples are equally likely to move following men's and women's layoffs.

We restrict our sample to the set of couples in which one person in the couple loses his or her job as part of a mass layoff. For the sample of mass layoff movers, the same age and student restrictions are imposed as described in section 2. Our sample includes about 11,000 layoffs in Germany and 15,000 in Sweden.

We show descriptively how men's and women's earnings and employment change following a mass layoff in Figure OA-3. For both men and women, wage income drops sharply the period of the mass layoff ($t = 0$). Men's income appears to recover to its $t = -1$ level about five years after the layoff whereas, for women, the recovery is slower (panels a and b).

In Table 3 we examine how the likelihood of moving depends on whether a man or a woman within a couple is laid off. We regress an indicator that takes the value one if a couple moves in the year of or the year after a mass layoff on indicators for either the man or the woman being laid off. We estimate this in a difference-in-differences framework, relative to "placebo layoffs" for men or women, to control for compositional differences between the couples in which a man is laid off or a woman is laid off.

Column 1 shows that in Germany, a man's layoff increases the probability of moving by 0.66 percentage points, a doubling compared to the mean of 0.72%. We can reject equality of the effects of moves after male and female layoffs with $p = 0.003$. Columns 2 and 3 show that the results are robust to controlling for age or age and commuting-zone fixed effects. Turning to Sweden, columns 4 to 6 show that the likelihood of moving also doubles when a man is laid off, increasing by 1.5 percentage points relative to a baseline moving rate of 1.46%. In contrast, the likelihood of moving slightly decreases or is unchanged when a woman is laid off. We can reject equality of the moving response to a male and female layoff with < 0.001.[16]

Table 3: Impact of Layoffs on Moving Probability

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Male Spouse Laid Off	0.66	0.56	0.56	1.47	1.48	1.46
	(0.15)	(0.15)	(0.15)	(0.19)	(0.19)	(0.19)
Female Spouse Laid Off	0.06	0.08	0.11	-0.29	-0.05	-0.06
	(0.14)	(0.14)	(0.15)	(0.13)	(0.13)	(0.13)
Age FE		✓	✓		✓	✓
CZ FE			✓			✓
N (Men Laid Off)	6176	6176	6176	8052	8052	8052
N (Women Laid Off)	4146	4146	4146	6768	6768	6768
Mean	0.72	0.72	0.72	1.46	1.46	1.46
M=W p-value	0.00332	0.0206	0.0264	<0.001	<0.001	<0.001
Observations	165449	165449	165449	263680	263680	263680

Notes: This table displays point estimates and standard errors clustered at the individual level (in parentheses) for the impact of layoffs for men and women on the probability of moving in t or $t+1$. The p-values refer to the test of whether the men and women layoff coefficients are equal. These regressions are run on the full sample of couples. All points estimates and standard errors are multiplied by 100.

Both our event study results and mass layoff results suggest that moves tend to benefit men. Several mechanisms could explain these results. First, the gender gaps could be due to women having lower earnings or lower earnings potential than men, so the gains from moving for the man's career are more likely to exceed the cost of moving. It could also be that, even if women's earnings are not currently lower than men's, couples anticipate that women will leave the labor force after having a child, resulting in lower future earnings.

[16]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. To address the possibility, Table OA-1 re-estimates the results re-weighting men and women to have the pre-layoff earnings and age distribution, as a proxy for occupation.

Another possibility is that women work in occupations with lower returns to moving. All of these explanations suggest that couples are behaving rationally and maximizing household earnings. An alternative explanation is that couples abide by a gender norm of prioritizing the man's career over the woman's career. In the next sections, we attempt to distinguish between men having higher potential earnings and a gender norm that prioritizes men's career advancement, arguing that the results are largely driven by the latter. We then test for alternative explanations, including anticipation of a "child penalty" and occupational differences.

5 Evidence of Norms: East and West Germany

We use couples' family origins as a source of variation in gender norms to test whether norms explain part of the earnings gap that emerges following a move. 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. 2021; Trappe 1996). This provides us with an ideal natural experiment in which we can compare couples current living in West Germany, and who therefore face similar institutions, but who vary in whether they are of East or West German background.

We follow Boelmann et al. (2021) and use the location of the first labor market entry 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 also restrict our sample of West German couples to those that have moved at least once before, since the East German individuals must have moved at least once to be in West Germany.

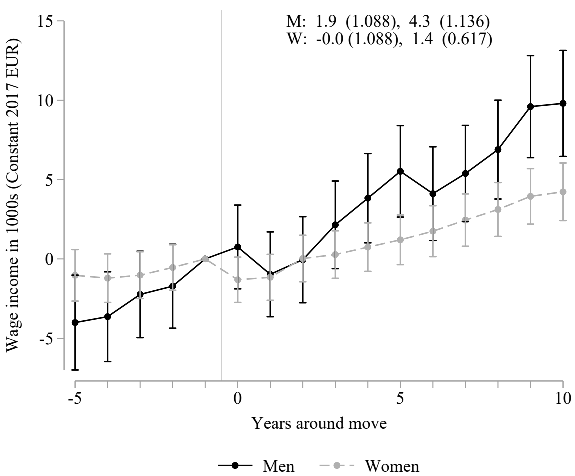
Figure 6 shows event study estimates for equation 1 for couples in which at least one spouse is of East German origin (panel a) and for those in which neither spouse of East German origin (panel b). The gender gap in earnings among couples in which neither spouse is from East Germany is large, with a long-run earnings gap of €7000. The gap is substantially smaller (€2700) among couples that have at least one spouse from East Germany.

In panels (c) and (d), we split the sample based on whether the man in the couple is of East German origin. Fernandez et al. (2004) present evidence that men who are exposed to a working mother have more liberal gender attitudes. Our results support this hypothesis and provide additional evidence of a gender norm. If the man is not of East German origin (panel d), the gender gap in earnings is large, but there is no gender gap if the man is of East German origin.

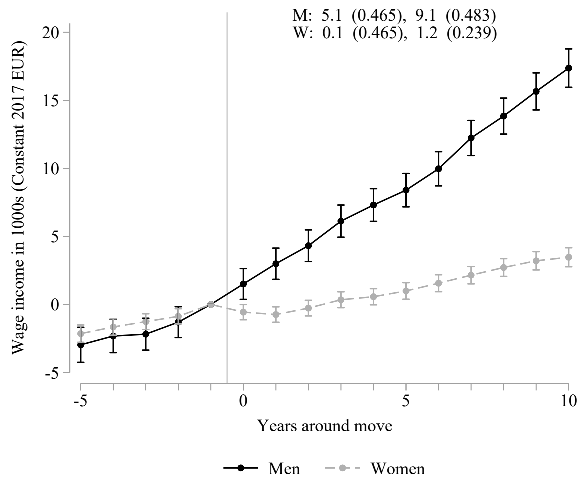
Since the couples in which a spouse is from East Germany have somewhat lower income, we re-weight the East and West German couples to have the same distribution of age and income (overall and by gender). The results in Appendix Figure OA-4 show similar patterns with this re-weighting, indicating that the small differences between the groups does not account for the patterns in Figure 6.

Figure 6: East vs. West German Origin

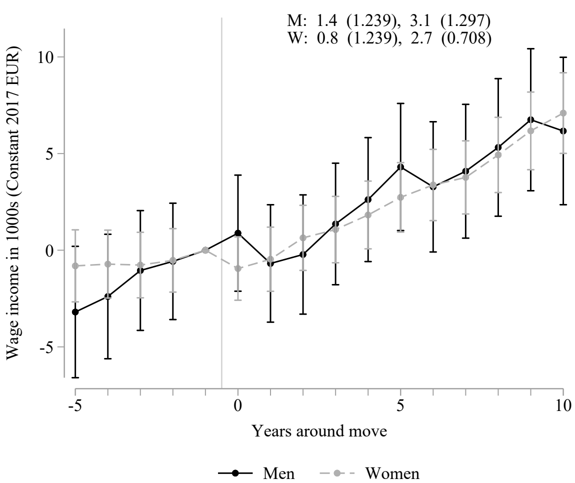
(a) At Least One Spouse East German Origin



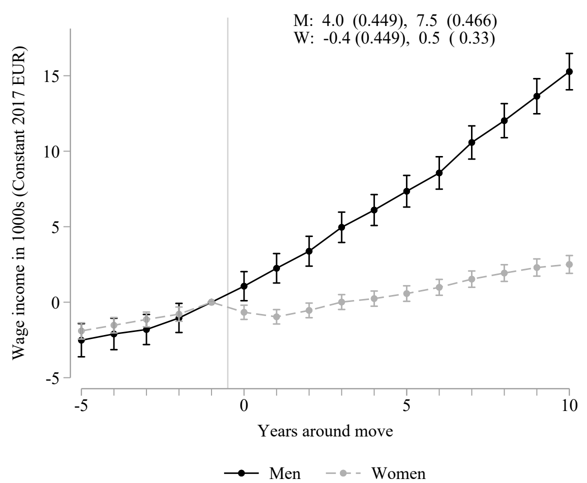
(b) No Spouse East German Origin



(c) Male Spouse East German Origin



(d) Male Spouse Not 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 place of birth 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 right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t = 0$ to $t = 5$ and $t = 10$), in this order, for men (M) and women (W).

6 Model-Based Estimation

The fact that the gender gap is substantially smaller for East German couples suggests that a gender norm is at play. We now set up and estimate a model to further distinguish between the two main explanations for our results: (1) men's higher potential earnings and greater returns to migration compared to women, and (2) a gender norm that prioritizes men's career advancement. To do so, we model household migration decisions by extending a standard model of collective decision-making (in which couples maximize household income) by allowing them to potentially place more weight on income earned by the man relative to the woman (Foged 2016). We use the model to derive additional empirical tests for whether or not the results in the previous sections can be rationalized with a standard collective model with gender differences in potential earnings.[17]

After presenting our theoretical results, we report additional empirical results that are directly motivated by the model, and we estimate the model parameters – separately for each country – using these additional empirical results and other moments from the data. We then use the model parameters to test (and reject) the collective model in both countries, finding larger deviations in Germany than Sweden. Lastly, we use the estimated

[17] Foged (2016) also develops a model where households discount income earned by the wife relative to the husband ($\beta < 1$), and we build on and extend this model in this paper. While Foged (2016) focuses on deriving predictions about how the probability of moving varies with the female earnings share of household income (determinants of moving), we focus on how the expected change in income after moving varies with the female earnings share (effects of moving). We show in the Appendix using simulations 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 or allowing for assortative mating; in particular, we find that the statistical tests in Foged (2016) can reject $\beta = 1$ when the true β is equal to 1 if either the pre-move income of women has higher variance than the pre-move income for men (which is empirically the case in our data for both countries), or if there is assortative mating (which has been documented previously in both countries (Henz and Jonsson 2003 and Blossfeld 2009). By contrast, in all of our simulations based on the empirical tests we develop and use, we only reject $\beta = 1$ when the true β is not equal to 1, and we never reject $\beta = 1$ when the true $\beta = 1$. As a result, we conclude that the earnings effects of migration are a more robust and reliable way to infer whether or not households actually discount income earned by the wife relative to the husband, compared to testing $\beta = 1$ based on the location of the minimum in the "U-shaped" relationship between mobility and the female share of household income.

model parameters to simulate the effects of job layoffs on migration and compare the simulated effects to the estimated effects of job layoffs documented above, and we also use the model to simulate the earnings effects of childbirth and compare the simulated effects to existing empirical estimates of the so-called "child penalty".

6.1 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 log-normal income distribution: $\log(y_{i1}) \sim N(\mu_i, \sigma^2)$.[18] With this setup, the average gender gap in period 1 is $E[y_{M1}] - E[y_{F1}] = \exp(\mu_M + \sigma^2/2) - \exp(\mu_F + \sigma^2/2)$. We define $s = y_{F1}/(y_{M1} + y_{F1})$ to be the female's share of total household income in period 1.

Migration decision. For simplicity, we assume that each household member receives the same income in period 2 as they received in period 1 if the household chooses not to move. Each household member independently draws a potential income in period 2 that they would receive if they choose to move move, with potential income $y_{i2} = (1+\varepsilon_{i2})y_{i1}$ and $\varepsilon_{i2} \sim N(\mu_r, \sigma_r^2)$. The μ_r and σ_r parameters capture heterogeneity in the returns to migration, and we assume that the average return to moving is the same across genders when expressed as a percentage of baseline income. We assume that a **collective household** chooses to move if and only if the increase in household income from moving is greater than the household's (money-metric) utility cost of moving c. We 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 $\Delta y_M + \Delta y_F > c$. A **non-collective household** places a different weight

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

on the female's income compared to the male's income, using a relative weight parameter β; this type of household will move if and only if $\Delta y_M + \beta \Delta y_F > c$. If $0 < \beta < 1$, then the household places less weight on the female's income compared to the male's income. If $\beta = 1$, then the household behaves as a collective household.

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

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

Proof. *See Appendix.*

This proposition shows that if there is a baseline gender gap (because $\mu_M > \mu_F$ implies $E[y_{M1}] - E[y_{F1}] > 0$) and the distribution of the potential returns to migration is the same for both genders, then in collective households, men will systematically benefit more from moving than women do. Intuitively, it is more likely that the male household member draws a potential income in period 2 that exceeds the household's cost of moving because the same draw in proportional income translates into a larger income gain in levels for him. Thus, conditional on moving, it is more likely that the move is a move that benefits the man rather than the woman. This implies that the previous reduced-form empirical results on their own do not reject a standard collective model and do not necessarily imply any inefficiency in household decision-making.

The full proof is given in the Appendix and uses the fact that the distribution of the female share of household income in period 1 follows a logit-normal distribution.[19] Some intuition can be gained from the following lemma:

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

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

Proof. *See Appendix.*

Lemma 1 says that for any household with $0 < s < 0.5$, the expected return to moving is larger for men than women. In the Appendix, we prove that if $\mu_M > \mu_F$, then $E[s] < 0.5$ in the population.[20] Thus, since the average household has $s < 0.5$ and all households with $0 < s < 0.5$ have expected return to moving larger for men then women, then it stands to reason that integrating across all households in the population will lead to an unconditional average return that is larger for men than women in the full population; this is the formal statement in Proposition 1.

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

Proposition 2 *If 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.*

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

Even if $\mu_M > \mu_F$, some households within the population will be at $s = 0.5$, and Proposition 2 shows that our model with collective households makes a sharp prediction for them. For these households, in which the two spouses have identical income in period 1 and the same distribution of potential returns to moving, the result is that it is equally likely that each member ends up being the "trailing spouse" when the household chooses to move. The man and woman are symmetric, so if $\beta = 1$, there should be no gender gap in the effect of moving on earnings.

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

We now turn to non-collective households, where households behave "as if" they put different weight on income earned by the woman relative to income earned by the man. We focus on the case where the households put less weight on income earned by the woman, so that $0 < \beta < 1$ (with $\beta = 1$ corresponding to the collective household benchmark). In contrast to Proposition 2, when households are non-collective households with $0 < \beta < 1$, the expected return to moving (conditional on moving) is larger for men than women at $s = 0.5$, with the gap decreasing as β approaches 1.

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.*

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

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

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

6.2 Heterogeneity in the Earnings Gap by Female Share of Household Income

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

In order to operationalize the additional empirical tests suggested by the model, we need to construct a measure of (predicted) female share of household income. To do this, we first estimate a Mincerian regression that we can use to assign a predicted income to each person in our sample. Specifically, we run a regression on a random sample of the full population of employed individuals (both full- and part-time) in each country aged 25-54. The regression model relates log 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 indicators for the college majors for the individuals who attended either college and vocational training , and we interact these college major indicators with the education dummies in the prediction model. For Germany, we use the 3-digit code of the first occupation instead of college majors.

We run this prediction model separately by gender so that we estimate predicted income from a gender-specific earnings model. This means that predicted income and our proxy for women's share of potential household income incorporate that households might expect women to earn less due to women generally being more likely to work part-time or due to employer discrimination. Moves favoring men due to these factors will load onto the collective-model interpretation. Our test of gender norms is a stringent one 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 these 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.[21] Figures OA-5 and OA-6 show the distribution of the resulting predicted incomes for the men and women in our sample, and the predicted female share. We use the predicted female share of household income ($\hat{s}$) as our empirical proxy for the s in the model.

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

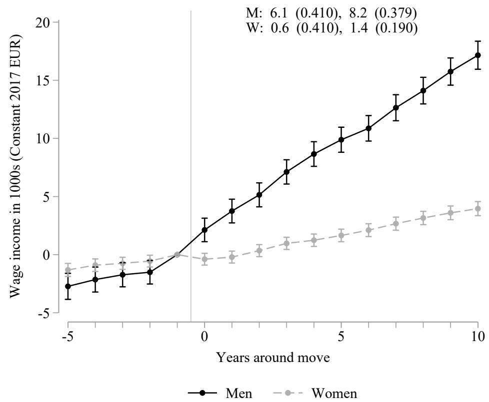
[21] We use the predicted female share rather than the actual share in part because our layoff results indicate a clear gender-specific effect of layoffs on the probability of moving, so women with very high household income shares in the years right before a move may be disproportionately made up of households where the man was recently laid off. In these households, the fact that the man disproportionately benefits from moving could mechanically come from mean reversion after the layoff event that occurred prior to the migration decision.

The results are shown in Figure 7 and point to an asymmetry based on whether the man or the woman is predicted to earn more. The gender gap in earnings is largest among the couples in which the woman's predicted household income share is smallest (panels a and b). Focusing on couples in which the man or the woman has a predicted earnings share of roughly 45-46%, we see that men benefit more on average from relocation than women for households with $\hat{s} < 0.5$ (panels c and d), but women do not benefit more from relocation than men for households with $\hat{s} > 0.5$ (panels e and f). Since these samples in the bottom four panels are constructed to have a equal and opposite predicted shares of household income, if the earnings gap were simply due to households maximizing joint income, we would expect to see the "equal and opposite" gender earnings gap among households in which women are predicted to earn more. Instead, we continue to see a gender earnings gap favorite men in Germany and no gender gap favoring men or women in Sweden in the subset of couples where the women are predicted to earn more. Taken together, these results provide clear evidence that $\beta < 1$ in both countries, with likely a bigger deviation from $\beta = 1$ in Germany because men *still* benefit more from relocation than women, even in households with $\hat{s} > 0.5$.[22]

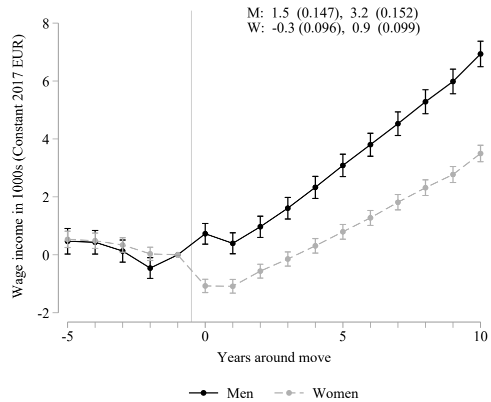
[22]In Figure OA-7, we report event-study results for moves with the female share of household income as an outcome across the same three groups, and we find clear evidence of a decrease in the female share of household income in both countries across all three groups.

Figure 7: Impact of Move on Wage Income – By Gender-specific Predicted Female Share of HH Income

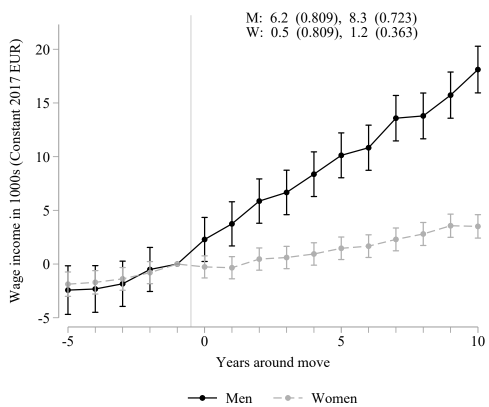
(a) $\hat{s} < 43\%$, Germany



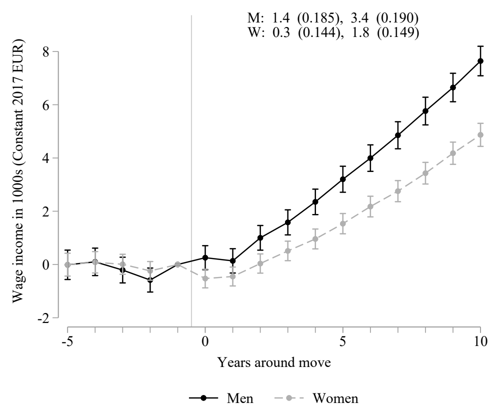
(b) $\hat{s} < 43\%$, Sweden



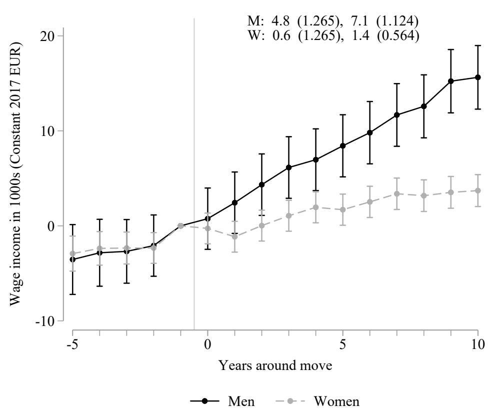
(c) $43\% \leq \hat{s} < 50\%$, Germany



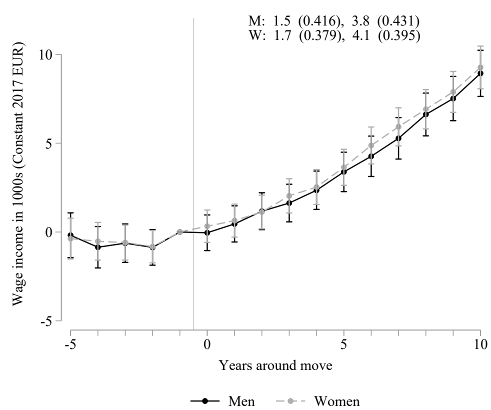
(d) $43\% \leq \hat{s} < 50\%$, Sweden



(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 right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t = 0$ to $t = 5$ and $t = 10$), in this order, for men (M) and women (W). Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old.

We summarize the results from the heterogeneity analysis in Table 4, which reports the effects of relocation on earnings for men and women in the full sample and in each of the three subsamples defined by $\hat{s}$. 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. Comparing across the columns, we see that in both countries in the two $\hat{s} < 0.5$ subsamples there are clear differences by gender. For these households, men's earnings increase by 10-15 percent in both countries, while women's income increase by much less.

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

	Germany		Sweden	
Predicted Female Share of Household Income, $\hat{s}$	Men (1)	Women (2)	Men (3)	Women (4)
Full sample	4.8 (0.3)	0.7 (0.3)	1.5 (0.1)	-0.1 (0.1)
$\hat{s} \geq 0.50$	4.8 (1.3)	0.6 (1.3)	1.5 (0.4)	1.7 (0.4)
$0.43 \leq \hat{s} < 0.50$	6.2 (0.8)	0.5 (0.8)	1.4 (0.2)	0.3 (0.1)
$\hat{s} < 0.43$	6.1 (0.4)	0.6 (0.4)	1.5 (0.1)	-0.3 (0.1)

Notes: This table presents estimates from spline regressions on the earnings effects of moving by gender, allowing for the effects of moving to vary with the gender-specific predicted female share of household income. The reported values correspond to the 6-year averages of the post-move point estimates, from $t = 0$ to $t = 5$.

Our main results are based on constructing $\hat{s}$ from gender-specific income prediction models. Alternatively, we could use a gender-blind income prediction model that assumes that women and men with identical education and experience have the same potential income. Appendix Figure OA-8 shows that this alternative yields broadly similar but slightly starker results (now even in Sweden, we find that men benefit more than women from relocation even when $\hat{s} > 0.5$). We prefer to use the gender-specific income predictions in our baseline analysis because we do not want other factors such as labor market discrimination to influence our estimate of β, as discussed above. By using a gender-specific income prediction, we assume that average gender gaps in income 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., for leisure. By assuming the average gender gaps do not arise from a norm to prioritize men's careers, we are using a conservative test when ruling out $\beta = 1$. This is because if households discount income earned by the woman, women might respond by working less or choosing lower-paying jobs, yet our gender-specific measure of potential earnings classifies those responses as lower potential earnings.

As a second alternative prediction model, we estimate a gender-specific Poisson model of earnings instead of an OLS model of log earnings, to incorporate observations with no earnings. Because the gender gap in non-employment is small (women's lower labor supply mostly takes the form of more part-time work), we find similar patterns with this alternative, as shown in Appendix Figure OA-9.

6.3 Model-Based Estimation

We now use the reduced-form estimates in Table 4 as moments to estimate the model parameters. We first calibrate the baseline distribution of income prior to migration in both countries. We do this by fitting a log normal income distribution for men and women in both countries based on the summary statistics in the year before the move. These results are reported in Panel A of Table 5. Consistent with the 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).

Table 5: Model Parameter Estimates

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Mean log income, men	3.63	3.42
Standard deviation of log income, men	0.55	0.43
Mean log income, women	2.78	2.68
Standard deviation of log income, women	0.64	0.53
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	-0.08	-0.09
	(0.07)	(0.06)
Standard deviation in the returns to migration, σ_r	0.15	0.11
	(0.05)	(0.05)
Household mobility cost, c	3.56	0.77
	(0.92)	(0.80)
Relative weight on woman's income compared to man's income, β	0.59	0.82
	(0.17)	(0.12)

Notes: Panel A displays the mean and standard deviation of log income in the year prior to the move for the full sample of movers. These values are used to calibrate the parameters of the log normal income distribution. Panel B displays the model-based estimates for both countries based on a simple equal-weighted minimum distance estimator, using as moments the average migration rate and the effects of moving for $0.43 \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 4.

With the baseline income parameters calibrated, 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 non-collective household parameter (β).[23]

To identify and estimate the four parameters, we use as moments four of the estimates in Table 4 which are the average change in income from relocation for men and women in two of the subsamples that group households based on $\hat{s}$ (the two with $\hat{s}$ closest to $= 0.5$ which refer to as the "symmetric split"). The fifth moment we use is the average migration rate that 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 9.1 percent in Sweden and XX percent in Germany. Intuitively, the identification works as follows: if $\beta = 1$, then the average change in income for men and women at $\hat{s} = 0.5$ should be the same according to Proposition 2. This tells us that the extent to which women do not benefit more than men in the $\hat{s} \geq 0.5$ 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 $0.43 < \hat{s} \leq 0.5$ 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

[23] In our baseline model, we assume that all households have the same mobility cost, but we can easily extend model to allow for heterogeneity in household mobility costs. Specifically, we can assume that household mobility costs are independently and normally distributed with parameters μ_c and σ_c. In our baseline model-based estimation, we use the average migration rate as an additional moment to estimate the mobility cost parameter. With additional migration data (e.g., migration rates for different subsamples of households), we would have additional moments to estimate σ_c separately from the other parameters. Importantly, whether or not we allow for heterogeneity in mobility costs, this does not affect the identification and estimation of the β parameter. One way to see this is that we can choose different values of migration rate and re-estimate the model and this shows no meaningful impact on estimates β parameter but it does affect the returns to migration parameters and the mobility cost parameter (see Table OA-2 for details). Because of this, we ignore heterogeneity in mobility cost for simplicity in our main analysis, since β is our primary parameter of interest.

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.[24]

To estimate the model parameters, we use a simulated method of moments approach which involves 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 each estimated moment. The Appendix provides more details on the estimation procedure, calculation of standard errors, and the over-identification tests we are able to do since we have more moments than parameters.[25]

[24] 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 small correlation across spouses in the returns to moving (see Table OA-3).

[25] While our main results are based on a standard simulated of method of moments algorithm, in the Appendix we show that we recover extremely similar estimates from an alternative two-step iterative estimation approach (see Table OA-4). In this approach, we first estimate the three model parameters other than β (i.e., the mean and standard deviation of the returns to migration and the mobility cost parameter) using three moments: the average earnings return for men and women in the $0.43 \leq \hat{s} < 0.5$ subsample and the migration rate. In the second step, we fix the three parameters besides β 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 and take the β from this second step and re-estimate the other three model parameters using the three moments from the first step, and continue 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 results for the $\hat{s} \geq 0.5$ subsample to the model-based predictions estimated for the full sample. We also report results which account for the fact that $\hat{s}$ is a noisy estimate by simulating a measure of predicted income that has the same R^2 as the actual R^2 in each gender-specific prediction model. This ensures that the simulated $\hat{s}$ has the same amount of noise as the empirical $\hat{s}$ used to define the subsamples for the reduced-form empirical analysis.The results in Table OA-5 show that we find similar estimates of the model parameters accounting for measurement error in $\hat{s}$.

The model parameter estimates are reported in Panel B of Table 5. The estimated distribution of the returns to migration is similar in both countries, with slightly greater dispersion in returns in Germany as compared to Sweden. We find larger mobility costs in Germany, although the baseline income is larger so as a percentage of baseline income, the mobility costs are more similar. The estimated household mobility cost is large in both countries, consistent with previous evidence that household migration is partly driven by income prospects but that households face large migration costs (see, e.g., Kennan and Walker 2011).[26]

Our primary parameter of interest is the β parameter, which is estimated to be $\beta = 0.82$ (standard error 0.12) in Sweden and $\beta = 0.59$ (standard error 0.17) in Germany. We can reject that $\beta = 1$ in Germany but we do not reject $\beta = 1$ in Sweden at conventional levels of statistical significance.

One way to assess the economic significance of $\beta < 1$ is to simulate the model with $\beta = 1$. Panel A of Table 6 shows the simulated moments at the estimated model parameters, and reports an extremely good model fit.

Panel B of Table 6 shows that imposing $\beta = 1$ (and holding other parameters constant) results in a somewhat worse model fit, particularly for the $\hat{s} \geq 0.5$ subsample. This restricted model is rejected at the 5 percent level in both countries. Lastly, Panel C of Table 6 reports results from an alternative approach that re-estimates the model restricting $\beta = 1$; this panel shows that this model also has a worse fit, particularly for Germany. The over-identification test continues to reject at the 5 percent level for Germany but it does not reject for Sweden, though the model continues predict that women benefit much more from migration than men in the $\hat{s} \geq 0.5$ subsample.

[26]Since the model is a two-period model, we can interpret the magnitude of the household mobility cost parameter as an approximate annual cost, which is estimated to be 3,560 euros in Germany and 770 euros 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 107,000 euros in Germany and 23,100 euros in Sweden. These 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 (or 265,000 euros at the 2017 USD-EUR exchange rate).

Table 6 also reports the simulated earnings effects of relocation for men and women in the untargeted $\hat{s} < 0.43$ 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 most gender-unequal households based on predicted female share of household income. Hence only use the "symmetric split" of households around $\hat{s} = 0.5$ to estimate β. The simulated model, using our parameter estimates, reproduces the large gender gaps in the $\hat{s} < 0.43$ subsample, though this is also true when we impose $\beta = 1$.

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, and the earnings effects at different predicted female shares of household income suggest that households in both countries place less weight on income earned by woman compared to man, particularly in Germany.

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

Table 6: Assessing Model Fit

Predicted Female Share of Household Income, $\hat{s}$	Germany Men (1)	Germany Women (2)	Sweden Men (3)	Sweden Women (4)
Panel A: Simulated Moments from Baseline Model				
Targeted Moments:				
$\hat{s} \geq 50$	6.3	1.9	1.5	1.7
$0.43 \leq \hat{s} < 0.50$	6.9	0.6	1.4	0.3
Household migration rate	0.091		0.091	
χ^2 [p-value]	0.0002 [0.989]		0.007 [0.934]	
Untargeted Moments:				
$\hat{s} < 0.43$	7.9	-0.4	1.8	-0.1
Panel B: Simulated Moments Setting $\beta = 1$ (holding other parameters constant)				
Targeted Moments:				
$\hat{s} \geq 50$	4.3	3.4	1.1	2.3
$0.43 \leq \hat{s} < 0.50$	5.7	2.2	1.2	0.6
Household migration rate	0.096		0.091	
χ^2 [p-value]	20.755 [<0.001]		4.739 [0.029]	
Untargeted Moments:				
$\hat{s} < 0.43$	7.5	0.6	1.7	0.1
Panel C: Simulated Moments Restricting to $\beta = 1$ (re-estimating other parameters)				
Targeted Moments:				
$\hat{s} \geq 50$	4.3	3.1	0.7	2.6
$0.43 \leq \hat{s} < 0.50$	6.8	0.5	1.3	0.4
Household migration rate	0.091		0.091	
χ^2 [p-value]	4.409 [0.036]		2.424 [0.119]	
Untargeted Moments:				
$\hat{s} < 0.43$	10.0	-2.0	2.1	-0.3

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 either holding other parameters constant or re-estimating the other model parameters. χ^2 is a goodness-of-fit statistic.

Table 7: Model-Based Simulations

	Germany		Sweden	
	Men	Women	Men	Women
	(1)	(2)	(3)	(4)
Panel A: Proportional Change in Probability of Moving After Layoff				
Empirical estimate	1.83	1.24	2.00	0.96
Model-based simulation	1.75	1.25	1.76	1.42
Panel B: Proportional Change in Earnings After Birth of First Child				
Empirical estimate from Kleven et al. (2019a)	-0.02	-0.61	-0.06	-0.26
Model-based simulation	-0.04	-0.53	-0.04	-0.20
Implied share of Female "child penalty" accounted for the country-specific β estimate		87.9%		76.9%

Notes: Panel A uses baseline model-based estimates to simulate changes in the probability of moving after an exogenous job displacement. The empirical estimates are calculated using the point estimates and mean from Table 3 columns (3) and (6). Panel B simulates change in earnings after birth of first of child to compare the implied changes (at estimated country-specific β) to the actual changes estimated in Kleven et al. (2019a). The last row is the quotient of women's model-based estimate and estimates from Kleven et al. (2019a).

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

An additional way to assess the fit of the model with the estimated $\beta < 1$ parameter is to simulate an exogenous decline in male or female income from an exogenous job separation, and then predict the change in the probability of moving depending on whether or not the male or female was laid off. We can then compare these results to the reduced-form estimates of the effects of job separations caused by mass layoff events. We view this as a useful "out-of-sample" test of model fit because the estimated effects of the mass layoff events on the probability of relocating by gender were not directly targeted in the model-based estimation.

For this exercise, we simulate the model at the parameters estimated in each country (reported in Table 7), 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 percent for men and 19.2 percent for women in Germany and 17.1 percent 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-specific or person-specific human capital, which does not change the return to migrating, but the remaining 25 percent of the earnings loss will be experienced if the worker remains in their current CZ but would not be experienced if they relocate.[27] The results in Panel A of Table 7 show that the model can accurately reproduce a large gender gap in the effects of a job layoff on the probability of moving. The model reproduces the reduced-form results fairly well, reproducing almost all of the gender gap in the probability of moving after layoff in Germany, but somewhat under-predicting the gender gap in Sweden. In Table OA-6, we show that when we impose $\beta = 1$ and re-simulated the model-predicted response to a layoff, we find a much smaller gender gap in the change in probability of moving after a layoff, suggesting that the $\beta < 1$ estimates in each country allow us to do a much better job predicting the observed gender gap in our mass layoff estimates. This exercise has obvious limitations: 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

[27]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.

from the actual reduced-form results. Given these limitations, the fact that our model does a fairly good job reproducing the results from the mass layoff analysis suggests that these other factors are likely less important than accounting for the non-collective nature of household decision-making captured by our $\beta < 1$ estimates.

As an additional application, we use our estimated model to simulate the change in earnings following the birth of a couple's first child to see how much our estimated $\beta < 1$ parameter can account for the female "child penalty" in both countries. Specifically, we compare our simulated results to the results from Kleven et al. (2019b) that estimate the child penalty in a large number of countries. They find that the child penalty is much larger in Germany than in Sweden, and we also find a larger departure from $\beta = 1$ based on the earnings responses to relocation. We therefore explore the possibility that the child penalty is partly due to households putting less weight on income declines by the woman (as compared to the man), even if the man and woman in a household have equal ability in child-rearing and equal preferences for reducing labor supply following the birth of their first child.

We provide the full details of the child penalty calibrations in the Appendix (see Section A.6), and we report results in Panel B of Table 7. Perhaps surprisingly, we find that we can quantitatively account for a majority of the previously-estimated child penalty in both countries. We do not fully account for the child penalty in either country, however, which could be due to other factors that we assume away in the exercise. For example, men and women may not actually have equal comparative advantage in child-rearing relative to market work and may not actually have equal preferences for spending time at home with children. That said, we view this stylized exercise as raising the intriguing possibility that the existing child penalty literature is primarily capturing a gender norm that prioritizes the man's career rather than these factors that we assume away in our simulations. Consistent with this tentative interpretation, we find that the gender gap in the earnings effects of relocation is smaller in couples in which at least one spouse is of East German origin, which lines up with previous work that has also found a smaller estimated child penalty in these same couples, compared to couples in which neither spouse is of East German origin (Boelmann et al. 2021).

7 Alternative Explanations

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

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

We test this possibility by restricting to couples that do not have a birth during our sample period. Figure 8 compares the event study results for couples that did not give birth during the sample period (panel A) and couples that did (panel B) for Germany. The long-run earnings gap between men and women is only slightly larger for couples with children (0.26 percentage points) than for couples without (0.22 percentage points). It is therefore unlikely that the anticipation of the "motherhood penalty" is driving the result.[28]

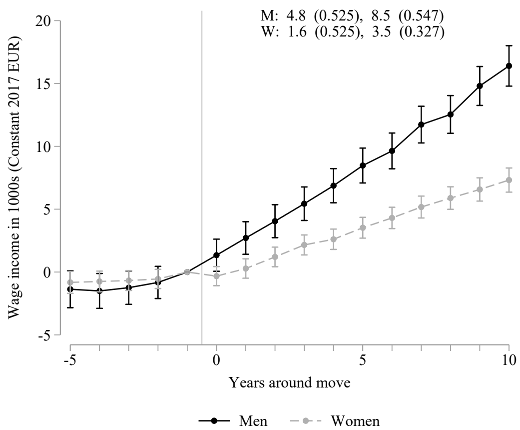
Occupation Selection Given that women tend to be in occupations with lower wage growth, it is possible that these same jobs have lower returns to moving. To test whether this can account for some of our main results, we estimate our event study equation but re-weight the sample so that women have the same occupation distribution as men.[29] We can only carry out this analysis in Germany because we have detailed occupation codes in the Germany administrative data but not in the Swedish administrative data. Appendix Figure OA-10 shows the results for the German couples for the three groups defined based on the women's predicted share of household income. We also include the unweighted regression results for comparison, and the results are very similar between the unweighted and re-weighted panels. We conclude from this that occupational sorting and differences in returns to moving by occupation are not driving our main results.

[28]In addition, the motherhood penalty may in itself be the result of a gender norm, as argued in Kleven (2023) and in Appendix Section A.6.

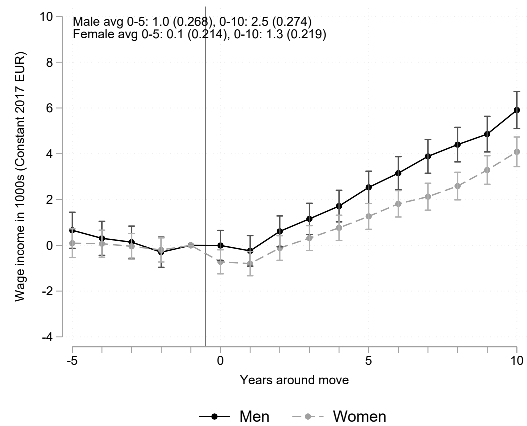
[29]To do this, we limit our movers sample to couples in which both individuals are working in occupations with at least 10 individuals in the occupation within our sample of movers. We further restrict to occupations that have at least one man and one woman. We then re-weight the sample so that the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

Figure 8: Wage Income Results by Children

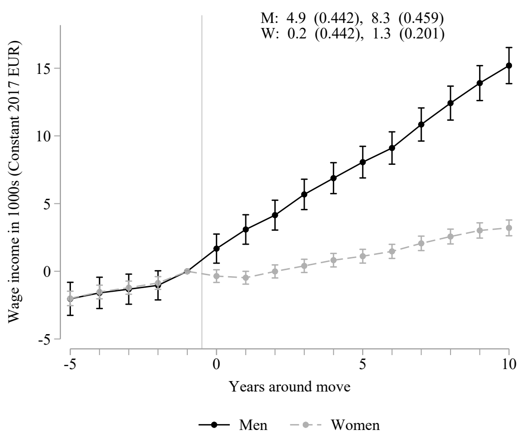
(a) No Children, Germany



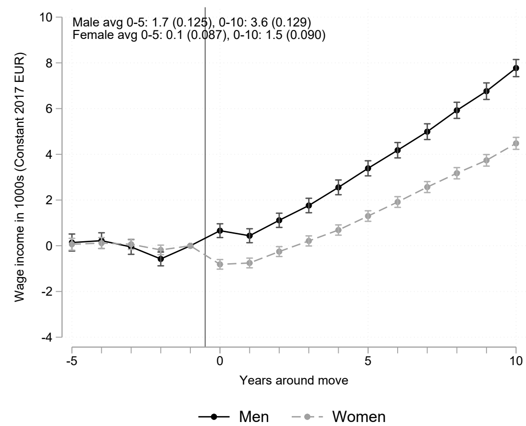
(b) No Children, Sweden



(c) Children, Germany



(d) Children, 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 ($t-1$) for different subsamples by country. Children means having birth in $t=-5$ to $t=10$, 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 right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W).

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 women benefit from a shorter commute whereas men benefit from a higher salary. To explore this possibility, we look at how distance to work changes following a move. Figure OA-11 shows that, while men's average commute increases slightly, women's average distance from work does not change. It is possible that women are moving to firms that are offering other non-wage amenities, but we are unable to test for this in our data.

Finally, couples could be moving to be closer to grandparents, to help with child-rearing, for example. This explanation would be in line with Anstreicher and Venator (2022), who find that American women tend to move back to their home locations in anticipation of childbirth. To explain the gender earnings gap that emerges in our case, it would need to be that couples only move to grandparents when the man can be compensated for doing so in the form of a higher wage, and that women do not work more or earn more in these areas. We can test whether couples move to live near grandparents using the Swedish data, where we can link family members over generations (we are unable to do so in the German data). Appendix Figure OA-11 shows no evidence that couples systematically move closer to any grandparent (or closer to a maternal grandparent).

8 Conclusion

Over the past half a century, there has been substantial gender convergence in the labor market, yet there are still large differences between men and women. In this paper, we investigate a phenomenon that contributes to gender gaps in the labor market that has not received much attention in the recent literature: gender differences in the returns to moving. Using administrative data from Germany and Sweden, we use an event study design to estimate the labor market effects of couples' long-distance moves, and we find that men's earnings increase significantly after a long-distance move, and women's earnings increase by less (if at all). These results echo some of the results in previous studies (see, e.g., Blackburn 2010a; Cooke et al. 2009; LeClere and McLaughlin 1997; Sandell 1977; Blackburn 2010b;

Cooke 2003; Spitze 1984; Rabe 2009), but the unusually large and representative sample of opposite-sex couples in our analysis and graphical event-study analysis provides new evidence of this gender divergence. While we find that men benefit almost exclusively through higher wages, women's losses are mostly due to exiting the labor market or being employed for fewer days in the year.

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

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

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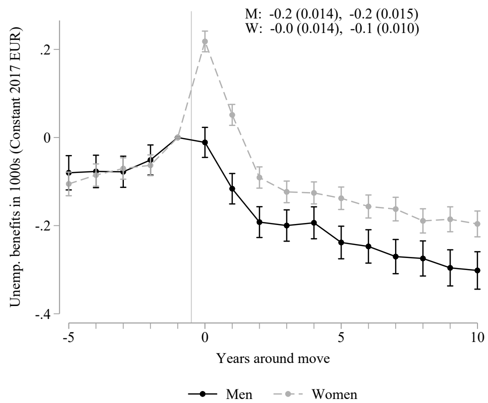
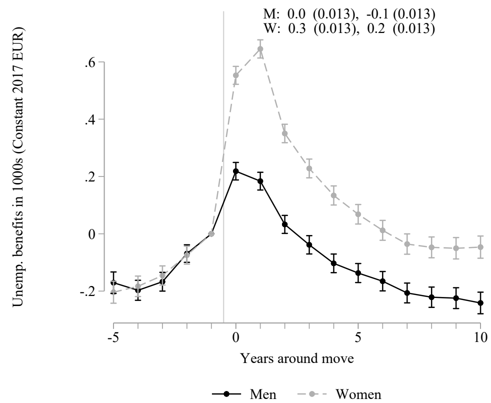
Online Appendix

Figure OA-1: Event Study Results on Other Measures of Employment

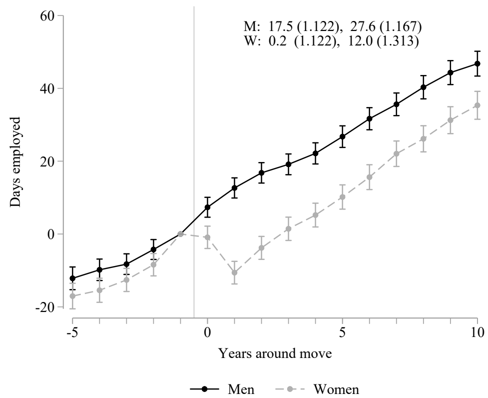
(a) Unemployment Benefits, Germany



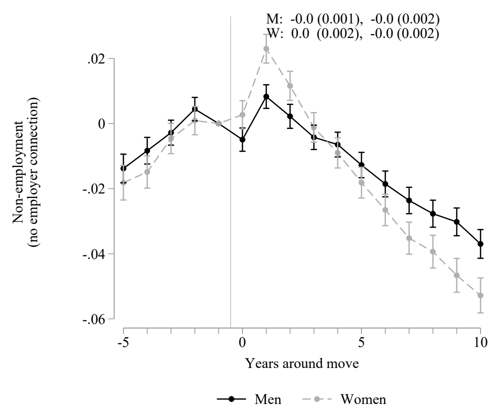
(b) Unemployment Benefits, Sweden



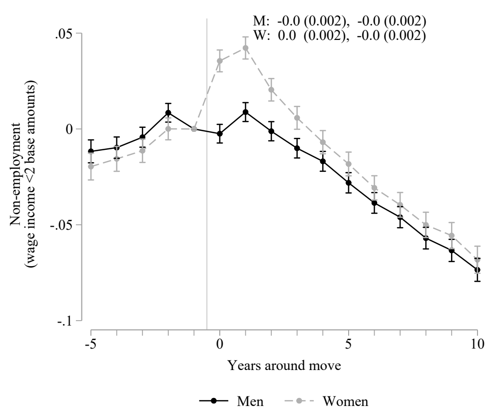
(c) Days Employed, Germany



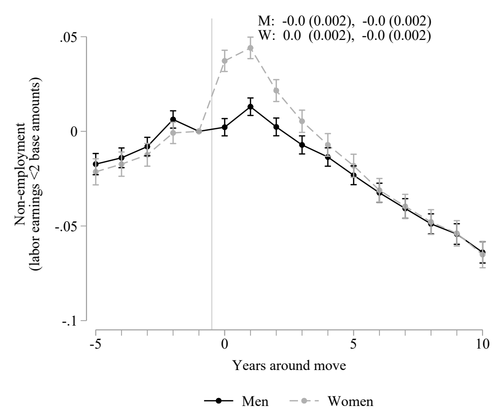
(d) No Employer Connection, Sweden



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



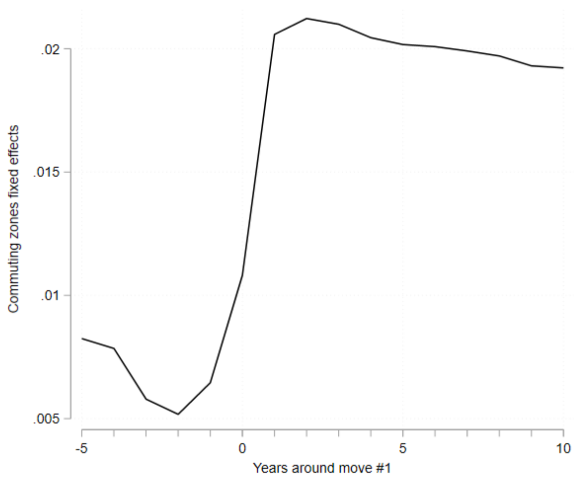
(f) Labor Earnings < 2 * Price Base Amounts, Sweden



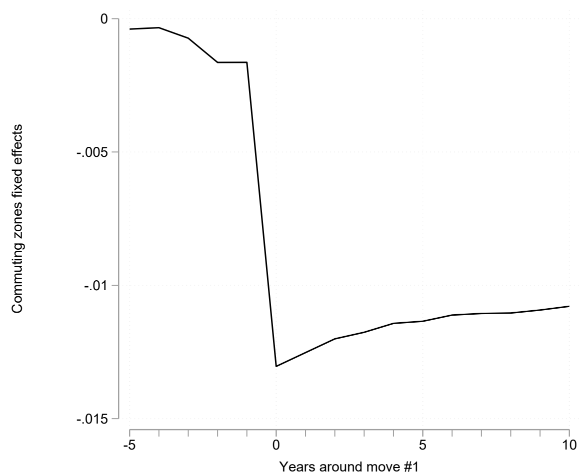
Notes: This figure displays the event study results that estimate the effect of moving on different outcomes in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The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

Figure OA-2: Commuting Zone Fixed Effects

(a) Germany



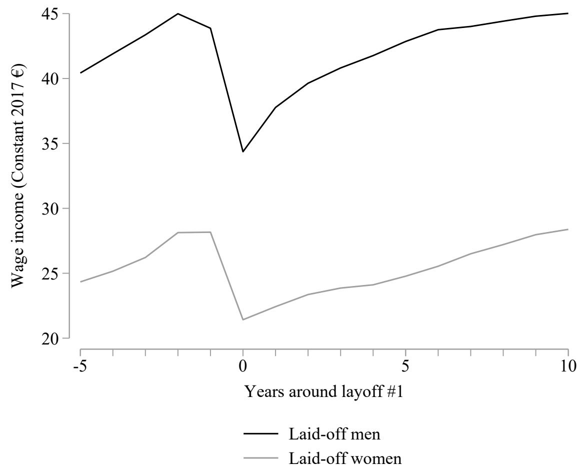
(b) Sweden



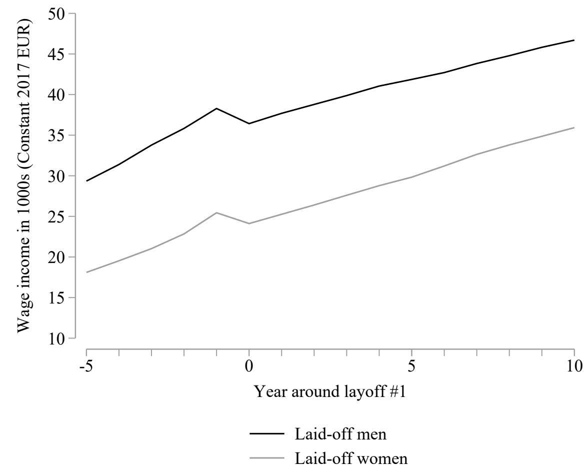
Notes: This figure displays the raw means of commuting zone fixed effects. We extract commuting zone fixed effects from a regression model relating log annual wage income to potential experience dummies, education dummies, year dummies, and commuting zone dummies.

Figure OA-3: Relationship between Layoffs and Labor Earnings and Employment

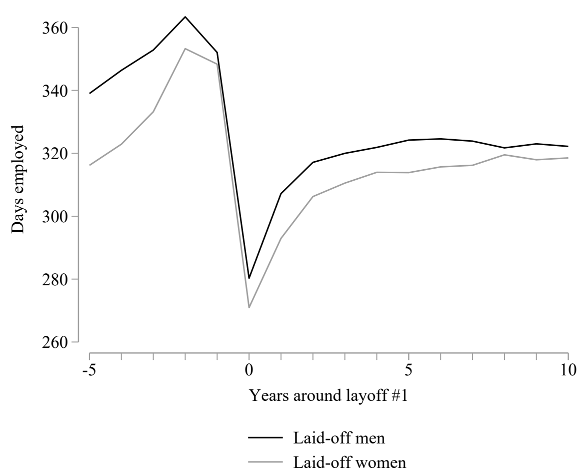
(a) Wage Income, Germany



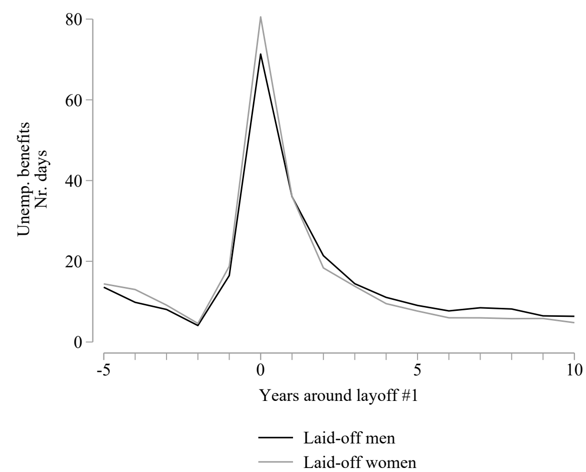
(b) Wage Income, Sweden



(c) Days Employed, Germany



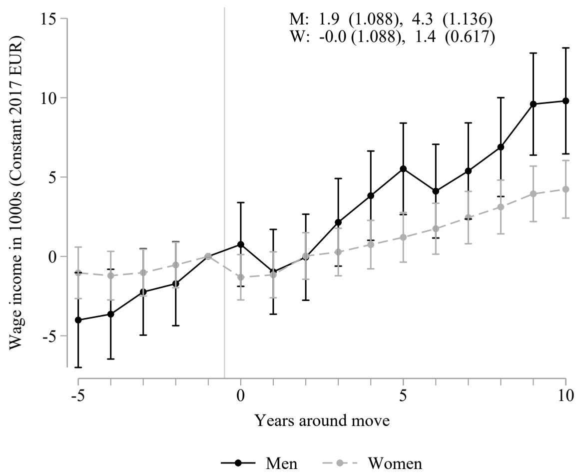
(d) Days UI Benefits , Germany



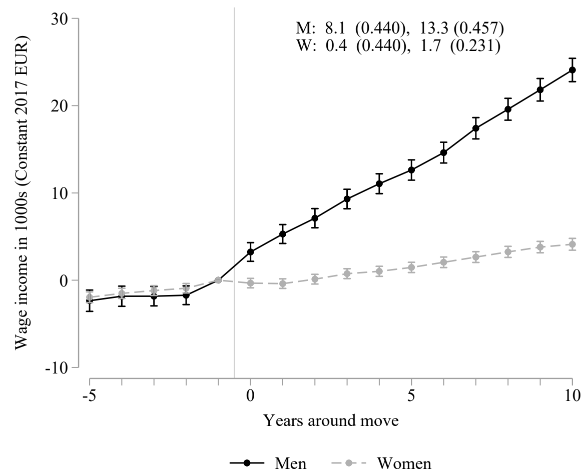
Notes: This figure displays means for different variables in each country from $t-5$ to $t+10$ relative to the first layoff event, per gender.

Figure OA-4: East vs. West German Origin – Reweighted

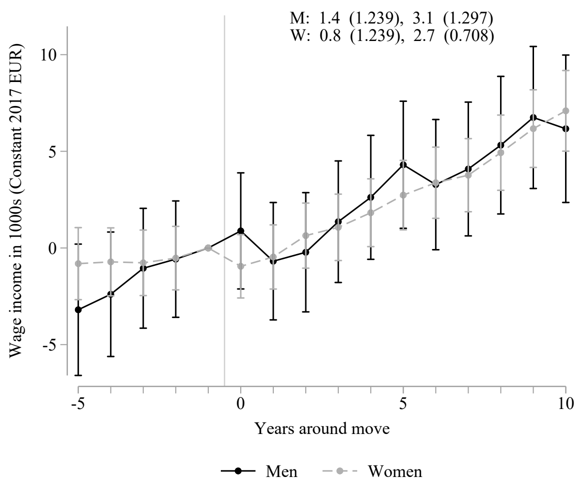
(a) At Least One Spouse East German Origin



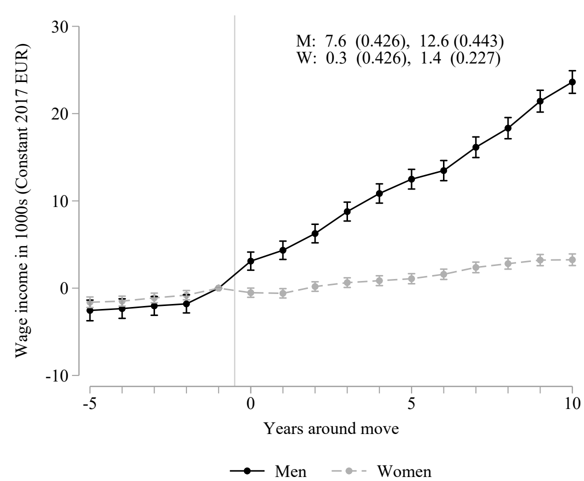
(b) No Spouse East German Origin



(c) At Least Man East German Origin



(d) Man Not 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 birth of one of the spouses or the male and are reweighted. We reweight couples in panel (b) and (d) to couples in (a) and (c), respectively (by pre-move wage income and age). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions are run separately by gender. The coefficients and standard errors (in parentheses) in the upper right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t=0$ to $t=5$ and $t=10$), in this order, for men (M) and women (W).

Predicted Income Methodology and Results

We use the following earnings prediction model:

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

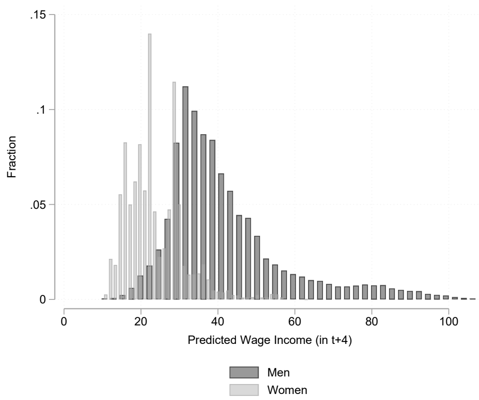
which controls for potential experience, number of children, college major (interacted with highest level of education), and year. In Germany, we do not have college major information so we replace with the highest level of education (three education categories: high school or less, vocational training,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

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

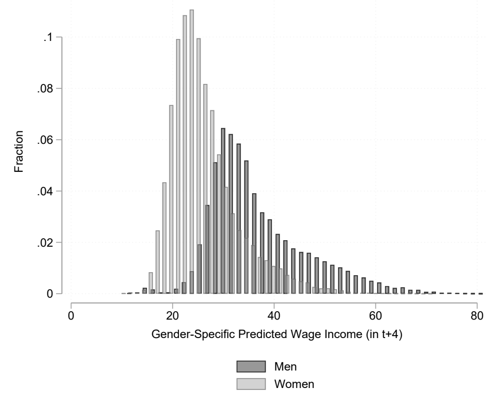
In the baseline analysis, we focus on *gender-specific* predictions so that the regression model above is run on men and women separately. We also report results using *gender-blind* predictions where the regression model is run on men and women together.

Figure OA-5: Predicted Wage Income, Movers

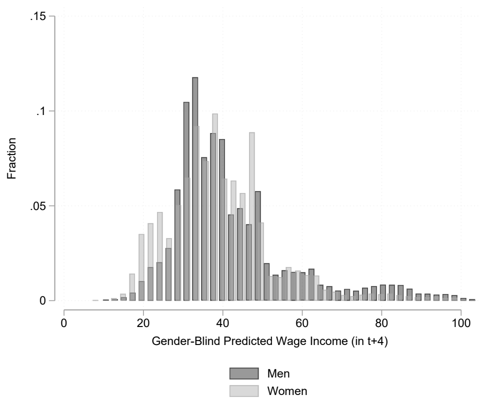
(a) Gender-specific, Germany



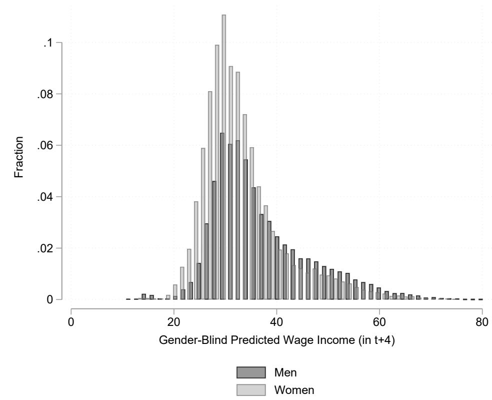
(b) Gender-specific, Sweden



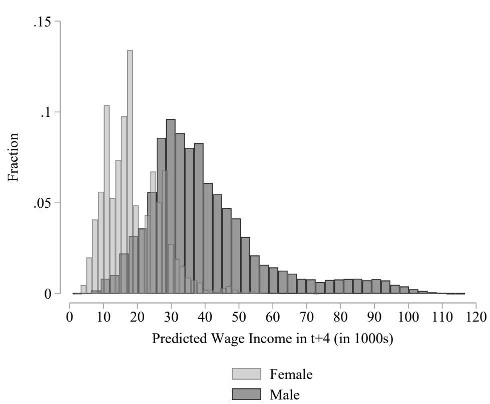
(c) Gender-blind, Germany



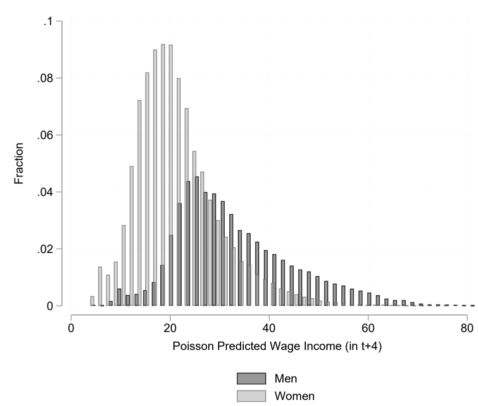
(d) Gender-blind, Sweden



(e) Poisson, Germany



(f) Poisson, Sweden

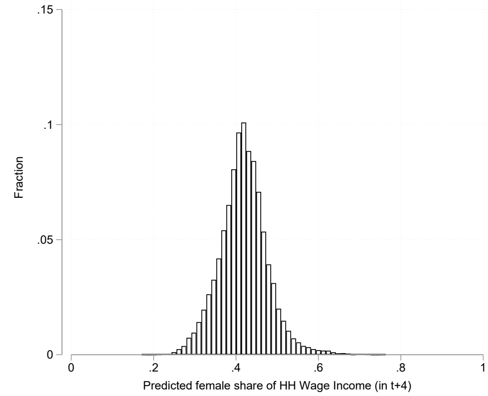


Notes: This figure displays histograms of predicted wage income by gender for each country on the movers sample. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. Gender-blind predicted earnings are calculated by regressing men's log individual income on experience indicators and education level interacted with field of study, in a way that men and women with the same covariates have the same predicted wage income. Predicted earnings using a poisson model include 0 earnings and 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.

Figure OA-6: Predicted Female Share of HH Income, Movers

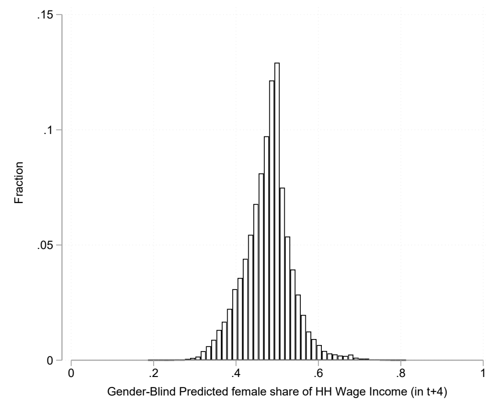
(a) Gender-specific, Germany

(b) Gender-specific, Sweden

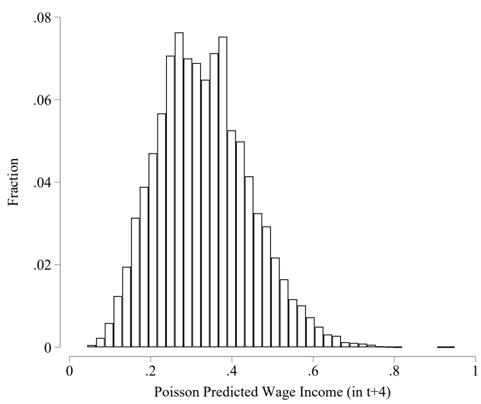


(c) Gender-blind, Germany

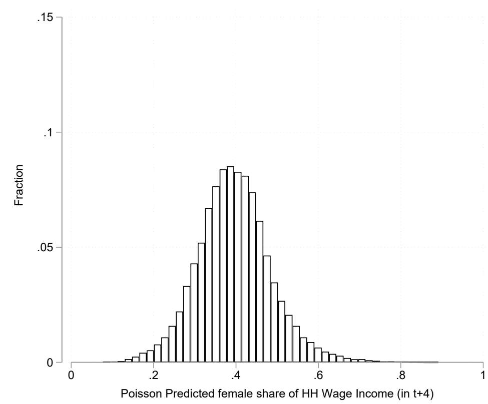
(d) Gender-blind, Sweden



(e) Poisson, Germany



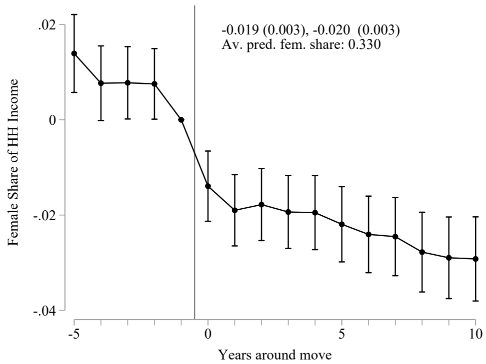
(f) Poisson, Sweden



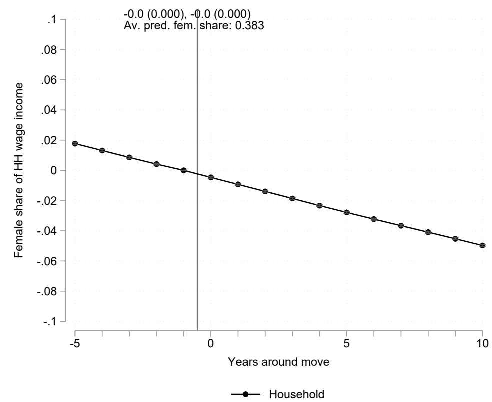
Notes: This figure displays histograms of predicted female share of household income by country on the movers sample. Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. Gender-blind predicted earnings are calculated regressing men's log individual income on experience indicators and education level interacted with field of study, in a way that men and women with the same covariates have the same predicted wage income. Predicted earnings using a poisson model include 0 earnings and 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.

Figure OA-7: Impact of Move on Female Share of HH Income – By Gender-specific Predicted Female Share of HH Income

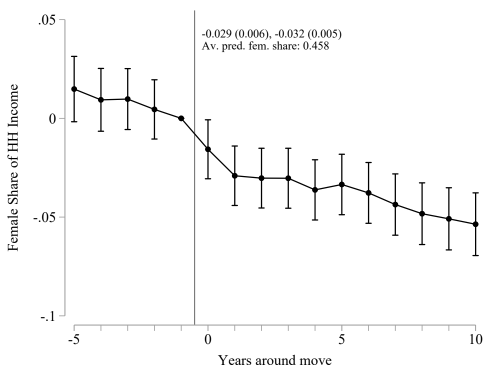
(a) $\hat{s} < 43\%$, Germany



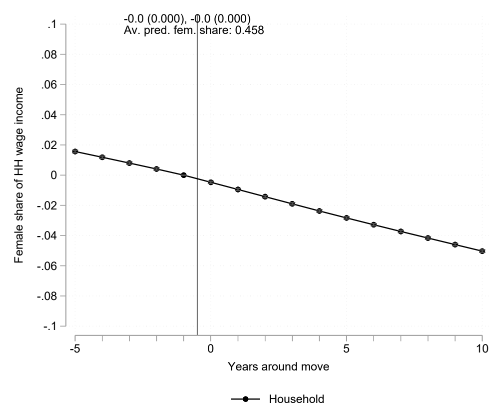
(b) $\hat{s} < 43\%$, Sweden



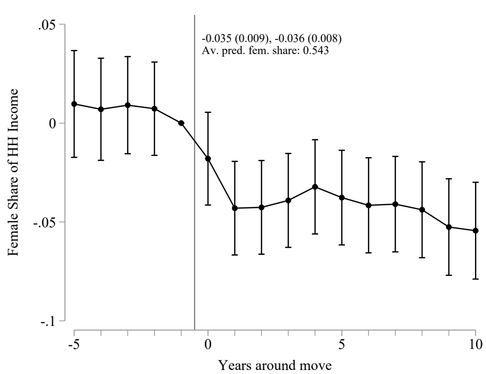
(c) $43\% \leq \hat{s} < 50\%$, Germany



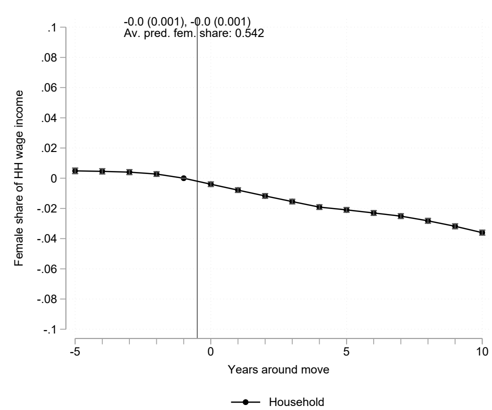
(d) $43\% \leq \hat{s} < 50\%$, Sweden



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



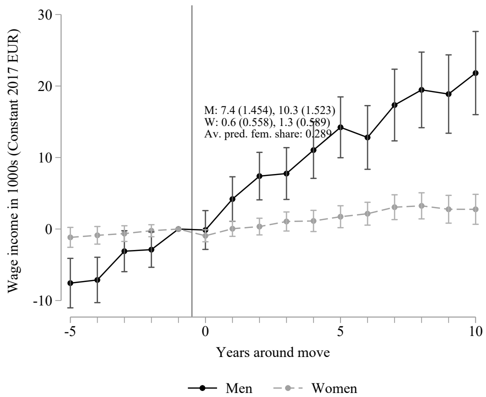
(f) $\hat{s} \geq 50\%$, Sweden



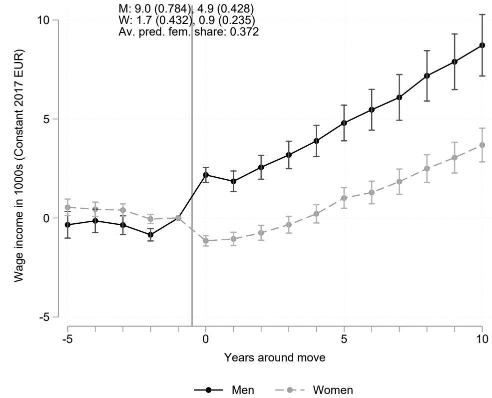
Notes: This figure displays the event study results that estimate the effect of moving on the female share of household income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual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

Figure OA-8: Impact of Move on Wage Income – By Gender-blind Predicted Female Share of HH Income

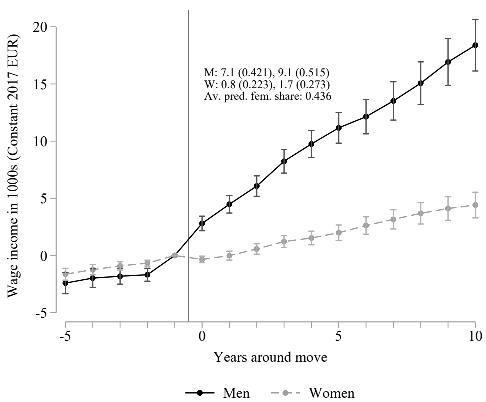
(a) $\hat{s} < 43\%$, Germany



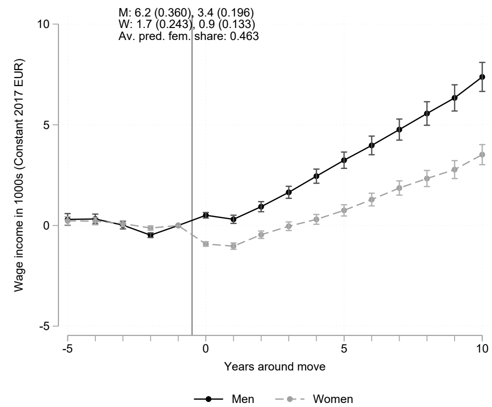
(b) $\hat{s} < 43\%$, Sweden



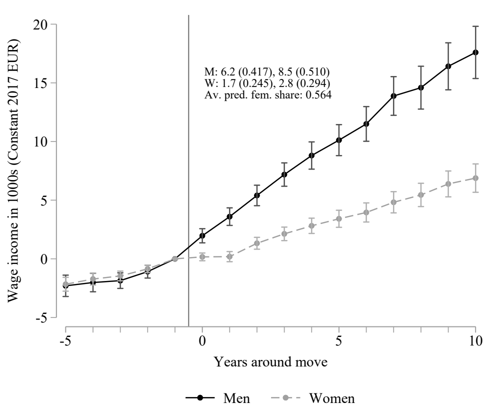
(c) $43\% \leq \hat{s} < 50\%$, Germany



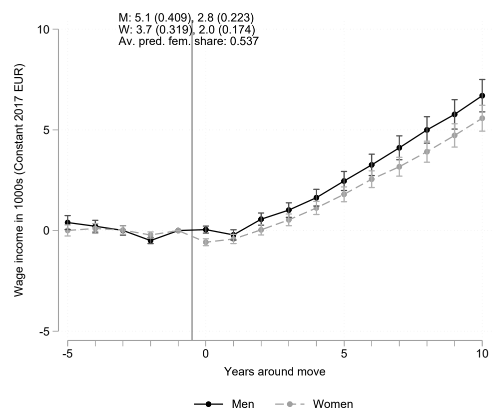
(d) $43\% \leq \hat{s} < 50\%$, Sweden



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



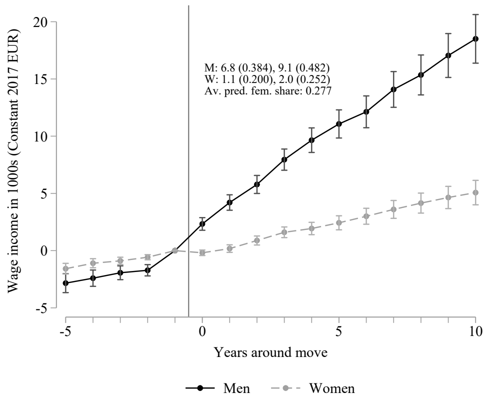
(f) $\hat{s} \geq 50\%$, Sweden



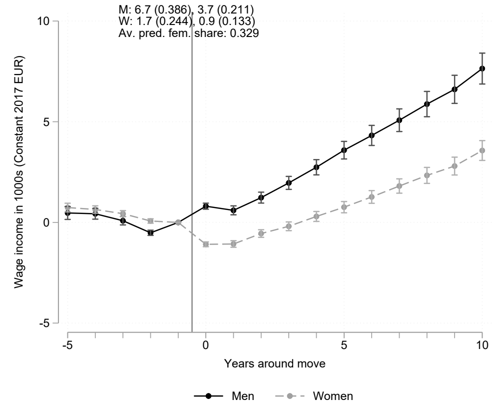
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions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

Figure OA-9: Impact of Move on Wage Income – By Poisson Predicted Female Share of HH Income

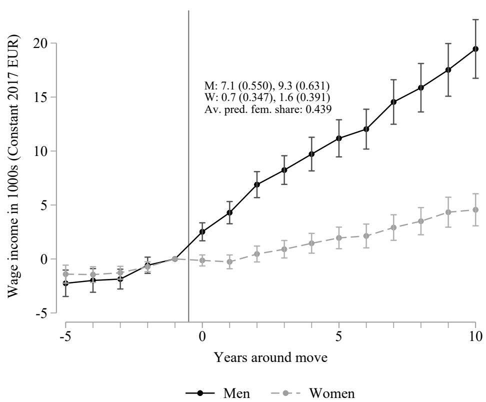
(a) $\hat{s} < 43\%$, Germany



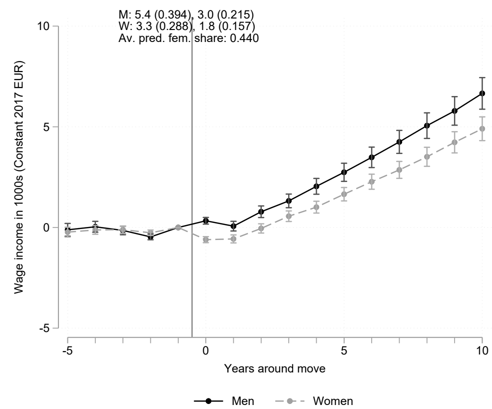
(b) $\hat{s} < 43\%$, Sweden



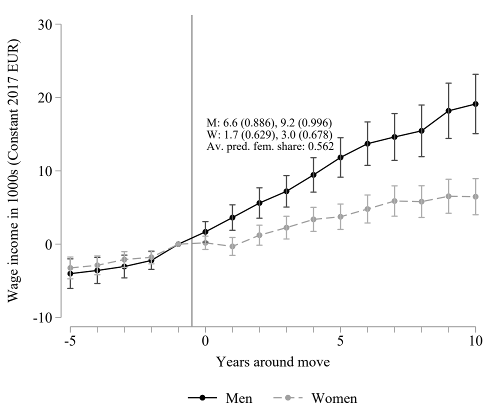
(c) $43\% \leq \hat{s} < 50\%$, Germany



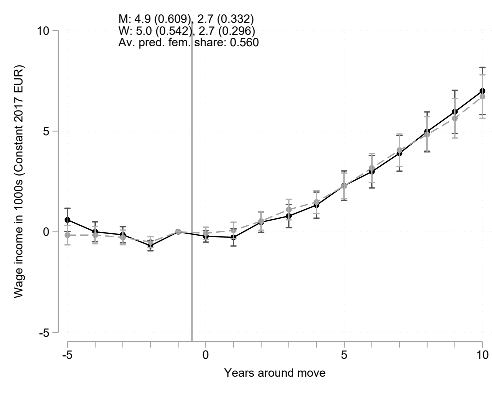
(d) $43\% \leq \hat{s} < 50\%$, Sweden



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



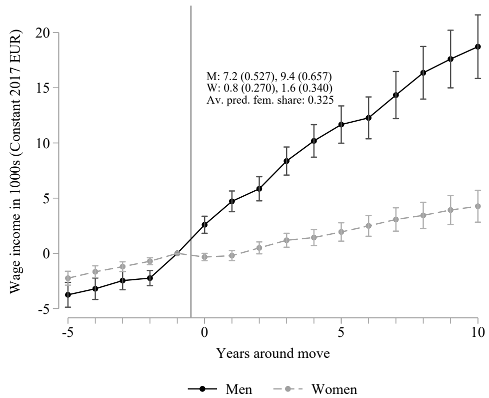
(f) $\hat{s} \geq 50\%$, Sweden



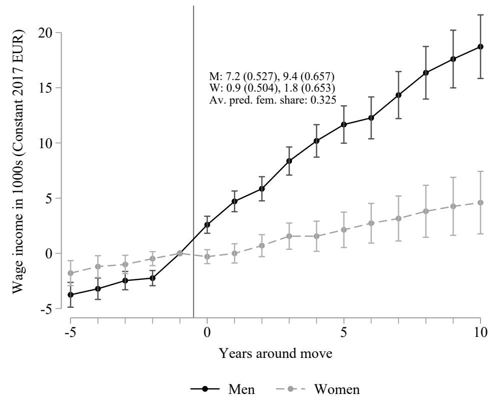
Notes: This figure displays the event study results that estimate the effect of moving on wage income in each year relative to the year before the move ($t-1$). Each point estimate has a corresponding 95% confidence interval calculated using standard errors clustered at the individual level. The regressions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

Figure OA-10: Occupation-weighted Impact of Move on Wage Income in Germany – By Gender-specific Predicted Female Share of HH Income

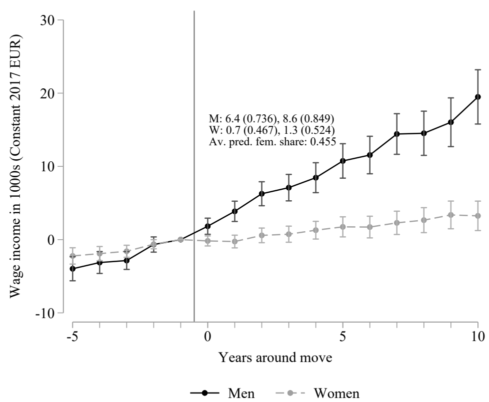
(a) $\hat{s} < 43\%$, Unweighted



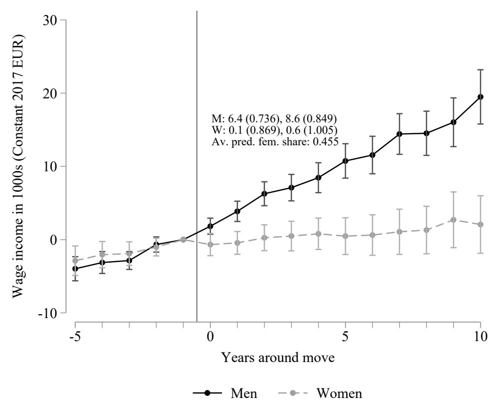
(b) $\hat{s} < 43\%$, Weighted



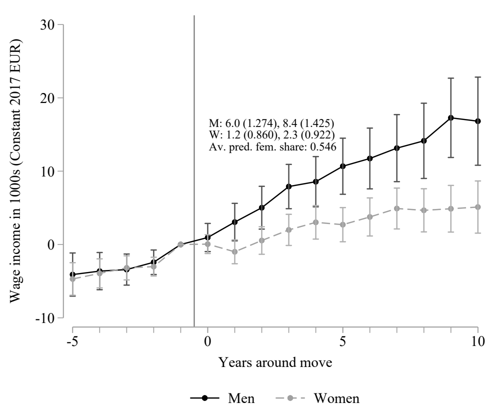
(c) $43\% \leq \hat{s} < 50\%$, Unweighted



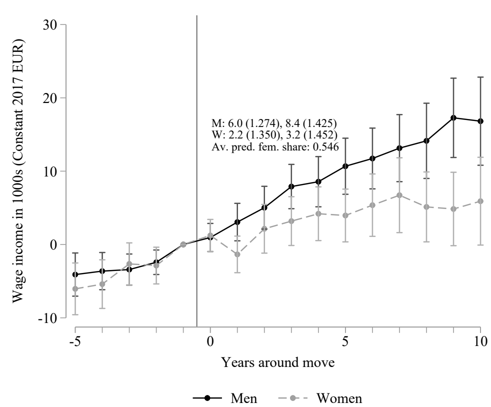
(d) $43\% \leq \hat{s} < 50\%$, Weighted



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

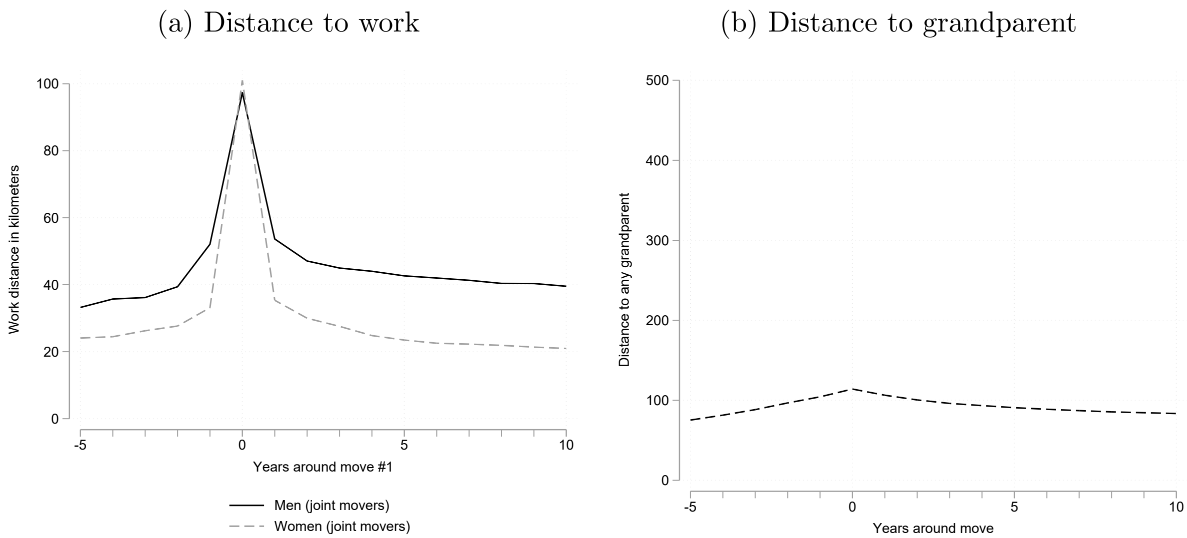


(f) $\hat{s} \geq 50\%$, Weighted



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 right corner of each figure are 6 and 11-year averages of the post-move point estimates (from $t = 0$ to $t = 5$ and $t = 10$), in this order, for men (M) and women (W). Predicted earnings share are calculated regressing log individual income on experience indicators, education level interacted with field of study, and an indicator on having a child under 19 years old. In panel (b), (d), and (f), we re-weight the sample so that women have the same occupation distribution as men using 4-digit occupation codes.

Figure OA-11: Amenities, Sweden



Notes: This figure displays the distance to the job by gender and the distance to the closest grandparent for the movers sample. Grandparents are defined as the spouses' parents, regardless of the couple having children or not.

Appendix Tables

Table OA-1: Impact of Layoffs on Moving Probability – Re-weighted Sample

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Male Spouse Laid Off	0.722	0.542	0.503	1.30	1.45	1.35
	(0.154)	(0.148)	(0.145)	(0.19)	(0.20)	(0.20)
Female Spouse Laid Off	0.0970	0.115	0.166	-0.405	-0.104	-0.153
	(0.157)	(0.158)	(0.166)	(0.15)	(0.16)	(0.17)
Age FE		✓	✓		✓	✓
CZ FE			✓			✓
N (Men Laid Off)	6176	6176	6176	8052	8052	8052
N (Women Laid Off)	4146	4146	4146	6761	6761	6761
Mean	0.723	0.723	0.723	1.46	1.46	1.46
M=W p-value	0.00333	0.0410	0.106	<0.001	<0.001	<0.001
Observations	158254	158254	158096	263363	263363	263363

Notes: This table displays point estimates and (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. We reweight couples where the woman has been laid off to couples where the man has been laid off based on pre-layoff wage income and age.

Table OA-2: Model Parameter Estimates' Sensitivity to Migration Rates

	Germany			Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline log normal income distribution parameters						
Mean log income, men		3.63			3.42	
Standard dev. of log income, men		0.55			0.43	
Mean log income, women		2.78			2.68	
Standard dev. of log income, women		0.64			0.53	
Panel B: Estimated model parameters						
Migration rate	$\times 1$	$\times 0.5$	$\times 2$	$\times 1$	$\times 0.5$	$\times 2$
Mean returns to migration, μ_r	-0.08	-0.07	-0.09	-0.09	-0.08	-0.09
	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Standard deviation in the returns to migration, σ_r	0.15	0.12	0.21	0.11	0.09	0.13
	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.06)
Household mobility cost, c	3.56	4.18	2.26	0.77	1.08	-0.02
	(0.92)	(0.77)	(1.33)	(0.80)	(0.66)	(0.99)
Relative weight on woman's income compared to man's income, β	0.59	0.60	0.59	0.82	0.81	0.82
	(0.17)	(0.15)	(0.18)	(0.12)	(0.12)	(0.11)

Notes: Panel A displays the mean and standard deviation of log income in the year prior to the move for the full sample of movers. These values are used to calibrate the parameters of the log normal income distribution. Panel B displays the model-based estimates for both countries based on a simple equal-weighted minimum distance estimator, using as moments the average migration rate and the effects of moving for $0.43 \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 4. For columns (2), (3), (5), and (6) we vary the migration rate to evaluate sensitivity.

Table OA-3: Model Parameter Estimates Allowing for Covariance Between Returns to Moving

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Mean log income, men	3.63	3.42
Standard deviation of log income, men	0.55	0.43
Mean log income, women	2.78	2.68
Standard deviation of log income, women	0.64	0.53
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	-0.19	-0.02
Standard deviation in the returns to migration, σ_r	0.22	0.06
Household mobility cost, c	2.31	1.73
Covariance in the returns to migration, $\sigma_{m,f}$	0.01	-0.002
Relative weight on woman's income compared to man's income, β	0.57	0.81

Notes: Panel A displays the mean and standard deviation of log income in the year prior to the move for the full sample of movers. These values are used to calibrate the parameters of the log normal income distribution. Panel B displays the model-based estimates for both countries based on a simple equal-weighted minimum distance estimator, using as moments the average migration rate and the effects of moving for $0.43 \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 4. Here, we allow for covariance between male spouse and female spouse returns to moving shock.

Table OA-4: Model Parameter Estimates from Two-step Estimation Approach

	Germany	Sweden
	(1)	(2)
Panel A: Estimated model parameters		
Mean returns to migration, μ_r	-0.08	-0.09
	(0.07)	(0.06)
Standard deviation in the returns to migration, σ_r	0.15	0.11
	(0.05)	(0.05)
Household mobility cost, c	3.56	0.77
	(0.92)	(0.80)
Relative weight on woman's income compared to man's income, β	0.59	0.82
	(0.17)	(0.12)
Panel B: Estimated model parameters with two-step estimation approach		
Mean returns to migration, μ_r	-0.12	-0.11
Standard deviation in the returns to migration, σ_r	0.17	0.12
Household mobility cost, c	2.89	0.50
Relative weight on woman's income compared to man's income, β	0.56	0.78

Notes: Panel A 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 $0.43 \geq \hat{s} < 0.5$ and $\hat{s} \geq 0.5$ reported in Table 4. Panel B displays the same results but using a two-step estimation approach.

Table OA-5: Model Parameter Estimates Accounting for Measurement Error in $\hat{s}$

	Germany	Sweden
	(1)	(2)
Panel A: Estimated model parameters		
Mean returns to migration, μ_r	-0.08	-0.09
	(0.07)	(0.06)
Standard deviation in the returns to migration, σ_r	0.15	0.11
	(0.05)	(0.05)
Household mobility cost, c	3.56	0.77
	(0.92)	(0.80)
Relative weight on woman's income compared to man's income, β	0.59	0.82
	(0.17)	(0.12)
Panel B: Estimated model parameters accounting for measurement error in $\hat{s}$		
Mean returns to migration, μ_r	-0.12	-0.11
	(0.07)	(0.06)
Standard deviation in the returns to migration, σ_r	0.17	0.12
	(0.06)	(0.05)
Household mobility cost, c	2.89	0.50
	(0.89)	(0.78)
Relative weight on woman's income compared to man's income, β	0.56	0.78
	(0.16)	(0.11)

Notes: Panel A 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 $0.43 \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 4. Panel B displays the same results but accounting for measurement error in the predicted female share of household income.

Table OA-6: Restricted Model-Based Simulations, $\beta = 1$ and Other Parameters Constant

	Germany		Sweden	
	Men (1)	Women (2)	Men (3)	Women (4)
Panel A: Proportional Change in Probability of Moving After Layoff				
Empirical estimate	1.83	1.24	2.00	0.96
Model-based simulation	1.58	1.47	1.70	1.60
Panel B: Proportional Change in Earnings After Birth of First Child				
Empirical estimate from Kleven et al. (2019a)	-0.02	-0.61	-0.06	-0.26
Model-based simulation	-0.05	-0.08	-0.04	-0.10
Implied share of Female "child penalty" accounted for the country-specific β estimate		13.1%		38.5%

Notes: Panel A uses baseline model-based estimates to simulate changes in the probability of moving after an exogenous job displacement. The empirical estimates are calculated using the point estimates and mean from Table 3 columns (3) and (6). Panel B simulates change in earnings after birth of first of child to compare the implied changes (at estimated country-specific β) to the actual changes estimated in Kleven et al. (2019a). The last row is the quotient of women's model-based estimate and estimates from Kleven et al. (2019a). For this table, we set $\beta = 1$ and hold other parameters constant.

Table OA-7: Restricted Model Parameter Estimates

	Germany	Sweden
	(1)	(2)
Panel A: Baseline log normal income distribution parameters		
Mean log income, men	3.63	3.42
Standard deviation of log income, men	0.55	0.43
Mean log income, women	2.78	2.68
Standard deviation of log income, women	0.64	0.53
Panel B: Estimated model parameters		
Mean returns to migration, μ_r	-0.36	-0.19
	(0.06)	(0.05)
Standard deviation in the returns to migration, σ_r	0.37	0.20
	(0.05)	(0.04)
Mean household mobility cost, μ_c	0.23	1.11
	(0.86)	(0.74)
Relative weight on woman's income compared to man's income, β	1.00	1.00

Notes: Panel A displays the mean and standard deviation of log income in the year prior to the move for the full sample of movers. These values are used to calibrate the parameters of the log normal income distribution. Panel B displays the model-based estimates for both countries based on a simple equal-weighted minimum distance estimator, using as moments the average migration rate and the effects of moving for $0.43 \leq \hat{s} < 0.50$ and $\hat{s} \geq 0.5$ reported in Table 4.

A Model Appendix

A.1 Proofs of Theoretical Results in Main Text

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

Proof.

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

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

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

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

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

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

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

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

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

Returning to integral A:

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

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

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

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

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

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

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

Plugging this back into integral A, we have:

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

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

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

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

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

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

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

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

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

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

Now looking at integral B:

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

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

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

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

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

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

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 $cov(X, Y) = 0$.

$$
\begin{aligned}
X &= \mu_r + \varepsilon_{M2} & Y &= \mu_r + \varepsilon_{F2} \\
&\sim N(\mu_r, \sigma_r^2) & &\sim N(\mu_r, \sigma_r^2) \\
(1-s)y_1X &= (1-s)y_1\mu_r + (1-s)y_1\varepsilon_{M2} & sy_1Y &= sy_1\mu_r + sy_1\varepsilon_{F2} \\
&\sim N((1-s)y_1\mu_r, ((1-s)y_1\sigma_r)^2) & &\sim N(sy_1\mu_r, (sy_1\sigma_r)^2)
\end{aligned} \tag{3}
$$

With this substitution, we can rewrite the expectation to be $E[mX - fY \mid mX + fY > c]$, which allows us to use the derivation from A.2.2, Equation (7).

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

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

The expression we end up with is given below:

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

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

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

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

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

Following the same steps to simplify the expectation as in 1, we get Equation (4) which is reproduced below.

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

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

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

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

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

We want to show that when $s = 0.5$, $E[\varepsilon_{M2}(1-s)y_1 - \varepsilon_{F2}sy_1 \mid s, \varepsilon_{M2}(1-s)y_1 + \beta\varepsilon_{F2}sy_1 > c] > 0$. We use the following substitutions, where $\varepsilon_{i2} \sim N(0, \sigma_r^2)$:

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

Rewriting the expectation to fit the form, $E[mX - fY \mid mX + bfY > c]$, and using the results from A.2.3, Equation (8), we plug in our substitutions for mX, fY.

$$
\begin{aligned}
E[mX - fY \mid mX + bfY > c] &= m\mu_X - f\mu_Y + \lambda(z)\left[\frac{(m\sigma_X)^2 - (bf\sigma_Y)^2 + 2\sigma_{mX,fY}(b-1)}{\sqrt{(m\sigma_X)^2 + (bf\sigma_Y)^2 + 2b\sigma_{mX,fY}}}\right] \\
\text{where } z &= \frac{c - m\mu_X - bf\mu_Y}{\sqrt{(m\sigma_X)^2 + (bf\sigma_Y)^2 + 2b\sigma_{mX,fY}}} \\
&= \lambda\left(\frac{c - 0.5y_1\mu_r - \beta 0.5y_1\mu_r}{\sqrt{(0.5y_1\sigma_r)^2 + (\beta 0.5y_1\sigma_r)^2}}\right)\left[\frac{(0.5y_1\sigma_r)^2 - (\beta 0.5y_1\sigma_r)^2}{\sqrt{(0.5y_1\sigma_r)^2 + (\beta 0.5y_1\sigma_r)^2}}\right] \\
&= \lambda\left(\frac{c - 0.5y_1\mu_r(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{(0.5y_1\sigma_r)^2(1-\beta^2)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right]
\end{aligned}
$$

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

$$
E[mX - fY \mid mX + bfY > c] = \lambda\left(\frac{c - 0.5y_1\mu_r(1+\beta)}{0.5y_1\sigma_r\sqrt{1+\beta^2}}\right)\left[\frac{0.5y_1\sigma_r(1-\beta^2)}{\sqrt{1+\beta^2}}\right] \tag{5}
$$

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:

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

$$= 0$$

A.2 Additional Theoretical Results

In the section below, general derivations are provided based on the following normally distributed random variables.[32] Let $X \sim N(\mu_X, \sigma_X^2)$, $Y \sim N(\mu_Y, \sigma_Y^2)$, $X + Y \sim N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2 + 2cov(X,Y))$, and c be a constant.

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

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

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

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

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

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

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

- Given a vector of random variables $X \sim N(\mu, \Sigma)$, then $AX + b \sim N(A\mu + b, A\Sigma A')$. Using this property, because X is normally distributed and $X+Y$ is normally distributed, we know that $\binom{X+Y}{X}$ are jointly normally distributed.

- Given $\binom{X}{Y} \sim N\left(\binom{\mu_X}{\mu_Y}, \begin{pmatrix} \sigma_X^2 & \sigma_{X,Y} \\ \sigma_{X,Y} & \sigma_Y^2 \end{pmatrix}\right)$, then $(Y \mid X = x) \sim N\left(\mu_Y + \rho_{X,Y}\left(\frac{\sigma_Y}{\sigma_X}\right)(x - \mu_X,), \sigma_Y^2(1 - \rho_{X,Y}^2)\right)$. Applying this property to X and $X+Y$, because they are jointly normal, we have $E\left[X \mid X+Y\right] = \rho_{X,X+Y}\left(\frac{\sigma_X}{\sigma_{X+Y}}\right)(X+Y) = \frac{\sigma_{X,X+Y}}{\sigma_{X+Y}^2}(X+Y)$.

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

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

Continuing the substitution,

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

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

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

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

$$
E\left[\frac{X}{\sigma_X} \mid \frac{X+Y}{\sigma_{X+Y}} > \frac{c-\mu_X-\mu_Y}{\sigma_{X+Y}}\right] = \rho_{X,X+Y} \frac{\phi(\frac{c-\mu_X-\mu_Y}{\sigma_{X+Y}})}{1-\Phi(\frac{c-\mu_X-\mu_Y}{\sigma_{X+Y}})} \tag{6}
$$

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

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

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

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

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

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

To simplify the second term above, we apply the result derived in A.2.1, Equation (6). Let $z=\frac{c-\mu_X-\mu_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2cov(X,Y)}}$ and $\lambda(z)=\frac{\phi(z)}{1-\Phi(z)}$.

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

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

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

Combining the terms together, we get:

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

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

$$E[X-Y|X+Y>c] = \mu_X - \mu_Y + \lambda\left(\frac{c-\mu_X-\mu_Y}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right)\left[\frac{\sigma_X^2-\sigma_Y^2}{\sqrt{\sigma_X^2+\sigma_Y^2+2\sigma_{X,Y}}}\right] \quad (7)$$

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

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

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

We start with defining the following random variables:

- $X = \mu_X + \varepsilon_X$ where $\varepsilon_X \sim N(0,\sigma_X^2)$
- $Y = \mu_Y + \varepsilon_Y$ where $\varepsilon_Y \sim N(0,\sigma_Y^2)$
- $bY = b\mu_Y + b\varepsilon_Y$ where $b\varepsilon_Y \sim N(0,b^2\sigma_Y^2)$
- $\varepsilon_X + b\varepsilon_Y \sim N(0,\sigma_X^2+b^2\sigma_Y^2+2bcov(\varepsilon_X,\varepsilon_Y))$

Deriving the first term, $E[X|X+bY>c]$:

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

To simplify the second term above, we apply the result derived in A.2.1, Equation (6). As in A.2.2, we let $z = \frac{c-\mu_X-b\mu_Y}{\sqrt{\sigma_X^2+b^2\sigma_Y^2+2bcov(\varepsilon_X,\varepsilon_Y)}}$, $\lambda(z) = \frac{\phi(z)}{1-\Phi(z)}$, and apply the same steps.

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

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

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

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

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

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

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

To summarize, the final derivation is given below:

$$E[X - Y \mid X + bY > c] = \mu_X - \mu_Y + \lambda\,(z)\left[\frac{\sigma_X^2 - b\sigma_Y^2 + cov(\varepsilon_X, \varepsilon_Y)(b-1)}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2b\sigma_{X,Y}}}\right]$$
$$\text{where } z = \frac{c - \mu_X - b\mu_Y}{\sqrt{\sigma_X^2 + b^2\sigma_Y^2 + 2b\sigma_{X,Y}}} \tag{8}$$

A.3 Model Extensions

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

Proof. Refer to A.1, Proposition 2.

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

Proof. Recall the substitution for mX and fY from Equation (3) 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 (4) 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 (4) above. The variances for X and Y do not depend on Period 1 variance, σ_i^2 for $i = \{M, F\}$, or any functional form assumptions on Period 1 income, so $\sigma_M^2 \neq \sigma_F^2$ would not affect the results and Proposition 2 still holds with heteroskedasticity in the first period.

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

Proof. Refer to A.1, Proposition 3.

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

Proof. From A.1, Proposition 3, the substitution for mX and fY remain identical to Equation (3). 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 (5), reproduced below:

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

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 (5) above. Again, the variances for X and Y do not depend on Period 1 variance, σ_i^2 for $i = \{M, F\}$, or any functional form assumptions on Period 1 income, so $\sigma_M^2 \neq \sigma_F^2$ would not affect the results and Proposition 3 still holds with heteroskedasticity in the first period.

A.4 Model-Based Simulations: 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 allow for assortative mating. The 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 the magnitude of the discount households place on 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 (1.) but $\sigma_F > \sigma_M$, 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 tables OA.XX 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 now 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.[33]

Appendix Table OA.XX 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 equal or unequal variances, and whether or not there is assortative mating.

Taken together, the results in Tables OA.XX and OA.XX 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 comparing house-

[33] 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.

holds with very different values of s that are otherwise very similar. Since in many settings households with different values of s will 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.

By contrast, our empirical approach requires "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 thus not based primarily on comparing *across* households, but rather 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 doesn't matter how the households are formed or how baseline income is drawn – as long as one can identify the households close to $s = 0.5$, then directly comparing the earnings returns for men and women is a direct test of $\beta = 1$.

A.5 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.

A.5.1 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

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 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 ($\widehat{p}$). We have formulas for these two moments:

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

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

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

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 $\mu_r = 0$ as a normalization, then it is straightforward to solve for parameters in terms of the empirical moments:

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

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. They also have intuitive comparative statics: holding constant σ_r, lower estimated migration probability leads to higher estimated migration cost parameter; and holding constant the migration probability, higher average earnings return leads to higher estimated variance in the returns to moving.

Household migration benchmark

Now we return to the baseline model of households making migration decisions, but 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 expression 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:

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

$$\widehat{p} = 1 - \Phi(z)$$

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 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 $z = \Phi^{-1}(1 - \widehat{p})$, then this can be substituted into the expressions for $\widehat{m_M}$ and $\widehat{m_F}$:

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

We can 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:

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

Since $y_M > y_F$, then the denominator in expressions for μ_r and σ_r is positive. The expression for $sigma_r$ implies that the percentage increase in earnings for men will always be larger than women and the larger the percentage gap, the larger the estimate of σ_r (holding constant baseline income and 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 game (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. Given μ_r and σ_r, then c is given by $\widehat{p} = 1 - \Phi(z)$.

All of the results for the individual migration model and the household migration model are presented given known income (y or y_M and y_F). With baseline heterogeneity in these values, the identification arguments 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 describe in the remainder of this section.

A.5.2 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 5. From this initial simulation we also end up with 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 step of 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 $0.43 \leq \hat{s} < 0.5$ 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 4), 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.[34] We define $\hat{\boldsymbol{\theta}}$ to be the parameter vector that minimizes m.[35]

A.5.3 Standard errors

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

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

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.

A.5.4 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.

A.6 Extended Model of the Child Penalty

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

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

subject to the budget constraint $c \leq w_M h_M + w_F h_F$, where w_M and w_F are the wage rates for the man and woman in the household, T is the total time endowment, 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.

[34] 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.

[35] 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.

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 in one way which is replacing c in the household utility function with $w_M h_M + \beta * w_F h_F$, and we calibrate the model using the estimated β from the model-based estimation.[36]

We choose $\eta_M = \eta_F = 1$, $\kappa = 0.2$, $\gamma = 0.5$, and we choose the baseline gender wage gap to be $w_F/w_M = 0.75$ in Sweden and $w_F/w_M = 0.85$ in Germany.[37] We then simulate the model for $\lambda = 0$ (no child) and $\lambda = 0.2$ (child) at the two different values of β and report the change in earnings for men and women in Table 7 in the main text. What 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.

[36]Note that this mathematically equivalent to assuming that the marginal utility of income is linear in income of each member of the household, and the marginal utility of income for the woman is β times the marginal utility of income of the man.

[37]In unreported results, we find that the results are not very sensitive to different assumptions on the gender wage gap, but we calibrate these values given the estimated β so that the earnings gap within the household (prior to first child) matches the gender earnings gap in our sample of movers without children in each country. Intuitively, we end up calibrating fairly similar gender wage gaps in both countries because in the Andresen and Nix (2022) model the woman will choose to work less the lower the value of β holding the gender wage gap constant.