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JEL Classification: D12, D13, J22

Keywords: time-use, spouses' labor supply, aggregation, Bayesian estimation

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Couples' Time-Use and Aggregate Labor Market Outcomes

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2021-06-08

Abstract

We present a model of the time-allocation decision of spouses in order to study the role of heterogeneity in preferences and wages for couples' labor supply. Spouses differ in their tastes for market consumption and non-market goods and activities, and also in their offered or earned wages. They interact in their choices of market hours, homework, and leisure. We estimate the model for married or cohabiting couples in the 2001/02 wave of the German Time-Use Survey using Bayesian techniques. We generate gender-specific own- and cross-wage elasticities of market hours in the cross-section. Elasticities are significantly larger if the wage shock is asymmetric across partners, not symmetric. Aggregating preferences and wages by gender and comparing outcomes for a representative couple with those from heterogenous couples yields a discrepancy between alternative aggregate wage-elasticities. Its size varies with the type of wage shock and the distribution of spouses across the preference-wage space.

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1 Introduction

The total supply of hours worked in the market is central to the production of goods and services. It varies not only across time, but at a given point in time it also depends on the underlying distribution of wage rates and reservation wage rates across the workforce. A change in either determinant affects the supply of total market hours. When an individual's labor supply interacts with that of her partner, her reservation wage rate depends not only on her own tastes and non-labor income, but also on her partner's wage rate. Since the bulk of market hours typically is supplied by individuals living in couples, the distribution of wage rates and reservation wage rates within and across couples therefore is an important determinant of total labor supply.

In this paper, we depart from the observed time-allocation of spouses in actual couples according to the German Time-Use Survey of 2001/02. In Germany, about two-thirds of individuals of prime working-age, i.e., between 25 and 54 years old are married or cohabiting. They are well represented

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in this survey. We measure the time they allocate across market work, homework, and leisure.[1] These couples display a wide variety of time-allocation choices. There co-exist dual-career couples, more traditional ones where the male works in the market and the female stays at home, less traditional couples with roles switched, as well as those where neither partner works. Figure 12 in the appendix illustrates that even within the couples with at least one spouse employed, the actual hours worked in the market and at home are very heterogeneous. We also measure the hours each individual contributes to home production. They matter for the total amount of goods available for consumption and for measuring leisure. Since the data report each activity in a broadly or a narrowly defined sense, we can distinguish, e.g., core home work from home work including childcare. Lastly, we have wage information for each employed person and non-labor income for each household.

The paper has three important contributions. First, we model individual heterogeneity in each partner's preferences and productivity and combine it with partners interacting in their time-allocation decisions. This generates as an equilibrium outcome single- and dual-earner couples and the empirically observed heterogeneity in market hours, homework, and leisure. Second, we structurally estimate these heterogeneous parameters for each couple, using a Bayesian multilevel model. Third, we use the estimated model for generating own- and cross-wage elasticities of market hours by gender in the cross-section and in two alternative aggregation scenarios. Aggregate wage-elasticities of market hours not only depend on the type of aggregation implemented, but also on the distribution of couples across the space of preference parameters and wage rates. Their size is larger in absolute terms when wage shocks are asymmetric — rather than symmetric — across spouses.

We take the observed heterogeneity in spouses' market hours and home work seriously when formulating a non-cooperative model of spouses' time-allocation decisions.[2] Our model features heterogeneity within and across couples in preferences and also in wage-rates. Each partner can split her available time between market work, homework, and leisure. A partner's choice depends not only on her respective preferences, market opportunities, non-labor income and constraints, but also on her partner's choices. By allowing partners to strategically interact in their time-allocation, they also interact in their goods consumption which comprises market goods and goods from home production. All agents endogenously sort into market work, or homework and leisure, yielding as equilibrium outcome dual-career couples, those with only one spouse employed, and couples where neither partner works in the market. The equilibrium is unique, but typically inefficient.[3] Throughout this paper, we take couples and their members' individual characteristics as given. In this sense, all of our results are conditional on the observed status quo processes of family formation, fertility, or education.

We implement the quantitative investigation by embedding the parameters of the structural model in a multilevel empirical model, and estimate them using Bayesian methods. The approach has

[1] All couples in our sample consist of a male and a female. To simplify language, we use partners and spouses interchangeably irrespective of their marital status. We commonly refer to the female partner as wife and to the male partner as husband. For similar reasons, we use the term *preferences* to capture actual preferences as well as other economic determinants of individual time-allocation not otherwise formulated in our model.

[2] Our model builds upon the analytical framework of Del Boca and Flinn (2012) who launched the idea of spouses interacting in their time-allocation.

[3] We have derived a variant of the model with an efficient equilibrium that solves a planner's problem, but introducing uniqueness requires an additional undetermined parameter. We do not consider this variant, since efficiency is not essential for what we do.

several advantages.[4] First, it allows us to handle the day-to-day variation of time use observations for the same couple as natural part of the empirical model. Second, the multilevel structure allows partial pooling of information from similar couples, sharpening our estimates for the parameters of each couple to the extent supported by the data, and also yields a posterior distribution for the wages of non-employed individuals jointly with other parameters. This allows us to make counterfactual predictions. Finally, calculating the counterfactuals we examine using posterior draws renders it particularly convenient to obtain posterior means of results even with the nonlinear mapping from couple parameters to the hours allocations.

The estimated model for our cross-section of couples serves as a point of departure for the subsequent analysis. First, we generate gender-specific own-wage and cross-wage elasticities of market hours in the cross section. Consistently producing these four types of wage-elasticities from one model is novel. We can do so, because our unit of analysis is a spouse within a couple. Gender-specific wage-elasticities of market hours matter for economic policies that aim at assessing the incidence of net wage changes, or their implication for time-allocation within and across couples. As we are using a static model, all elasticities are of Marshallian type. They measure the induced change in market hours by individuals who were previously employed or non-employed. We can disentangle the relative importance of single- and dual-earner couples and also the direction and size of each partner's hours adjustment in reaction to wage shocks. The bulk of changes in market hours occurs among dual-career couples.

Our cross-sectional estimates anchor our work in the respective microeconometric literature, e.g. Blundell and MaCurdy (1999), or Blau and Kahn (2007), since they are of plausible size and show a similar pattern: females' wage-elasticities in absolute terms exceed by far the male counterpart, and own-wage elasticities decline in the wage rate. Moreover, all elasticities are an order of magnitude larger when generated from an asymmetric rise in either the male or the female wage-rate than when both wages rise symmetrically. This result is due to spouses mutually insuring variations in income which matters most when wage-shocks are asymmetric. Males' mean own-wage elasticity equals 0.4. It is the weighted average of a higher elasticity for men in dual-career couples and a much smaller elasticity for those in traditional ones. The situation for females is different. Their mean own-wage elasticity is significantly larger at 1.03. It equals the weighted average of a very high value for the many women in dual-career couples, an even larger value for the few in traditonal couples who start employment, and a much smaller one for single-earner women.

Second, we aggregate preferences and wage rates. Quantitative macroeconomic models usually face a trade-off between capturing cross-sectional heterogeneity and using simplifying assumptions such as a representative agent, or more generally a set of parameters common to all agents, which are simpler to solve and estimate. The rich cross-sectional structure of our model allows us to investigate this trade-off by addressing the implications of homogeneous wages, preferences, and both for each gender. Specifically, we aggregate preferences and wage rates by gender and compare the implied aggregate wage-elasticities of market hours with those from an alternative setup we label *representative couple*. It is defined as the couple characterized by preference parameters and wage rates for each

[4] Section 5.3 explains how we obtain good mixing and convergence using the NUTS sampler with a custom transformation.

partner such that the implied time-allocation and earnings replicate the gender-specific (weighted) average counterpart in the data. When comparing a particular wage-elasticity across these two alternative aggregation scenarios, a discrepancy arises which we call *aggregation bias.* We study how this bias reacts to symmetric or asymmetric wage changes for males and females in order to explore the quantitative role of spousal mutual income insurance.[5] Decomposing the bias lets us identify the couple types that matter most for the various biases. We define a couple's type by each partner's labor market status and the relative position in the joint distribution of preference and wage parameters.

Comparing the implied aggregate wage-elasticities across the two alternative aggregation scenarios yields a bias of about 56 percent for own-wage elasticities and 73 percent for cross-wage elasticities. Those discrepancies are similar across men and women for a particular wage-elasticity, but they can reflect very different underlying patterns of adjusting hours worked for either gender. We elicit the components of all biases that are due to preference aggregation only, or wage aggregation only in order to identify the couple types whose reactions matter most for the observed discrepancies. The exact size of the measured discrepancies depends on the distribution of various couple types across the space of preference parameters and wage rates. To illustrate this, consider the bias of 56 percent for own-wage-elasticities. For men, it is driven by those who highly value market consumption, have a below-average wage rate and live in dual-earner couples. Preference aggregation induces them to reduce market hours which increases their own-wage elasticity. When wages are subsequently averaged, they raise their market hours, thereby counteracting the initial rise without overturning it. For women, the same bias is determined by those who highly value market consumption and have a below-average wage rate. When living in a dual-career couple, preference aggregation induces them to lower market hours or stop market work altogether which lets the own-wage elasticity rise. This effect is enhanced by females with an initially high wage that declines following wage aggregation.

The paper proceeds as follows. Section 2 relates to the literature. Section 3 introduces details of the German Time-Use Survey. Section 4 presents the model setup, while Section 5 lays out the estimation strategy. Section 6 discusses the results and their robustness. Finally, Section 7 concludes.

2 Related Literature

Our work relates to the growing literature that studies the time-allocation of couples and considers quantitative implications for the aggregate economy. This literature emphasizes the importance of wage-elasticities of labor supply for policy makers, and that those elasticities vary with the chosen modeling framework. The contributions on the topic differ from each other with respect to the type and extent of heterogeneity, the details of the decision-making process including the relevant time horizon, and closely related decisions such as education, mating / marriage, or fertility which may be explicitly considered.

Many papers on couples' time-use that aim at explaining economic aggregates use a unitary model, thereby implicitly assuming that all household members have identical preferences and share the same objective and constraints.[6] According to this modeling approach, heterogeneity

[5]The detailed results are summarized in Table 5 through Table 7.

[6]Examples include Rogerson (2008) who studies the role of labor income taxes and labor productivity in explaining

relates to couples, not to the individual partners. It is a commonly used approach in the part of the literature on couples' time-allocation that focuses on family labor supply in the cross-section.[7] By now equally common are household models which explicitly consider individual members with their respective objectives and constraints and allow them to interact. They comprise cooperative and non-cooperative versions, but do not specify the bargaining process between family members. They instead generate allocations that can be interpreted as if bargaining had occurred. Cooperative models consider marriage as a cooperative game where spouses settle on outcomes that are Pareto optimal, whereas non-cooperative models view partners as acting strategically and voluntarily settling on an inefficient equilibrium.[8] Goussé, Jacquemet, and Robin (2017) use a static collective model of household consumption and individual time-allocation. They endogenize the sharing-rule which determines a couple's internal distribution of power by explicitly modeling the match formation of single males and females and allowing for their dissolution. They estimate the model with the help of data from the British Household Panel Survey from 1991 to 2008 and retrieve Marshallian style own- and cross-wage elasticities for male and female hours worked in the market and at home. They investigate how family values affect the mating and time-allocation decisions.

We share the static interactive household setup, but depart from a non-cooperative setting where we take married couples as given. We build on and extend the existing literature in two important ways. First, we model individual heterogeneity in each partner's preferences and productivity. Combined with partners interacting in their time-allocation decision, this leads to couples who endogenously sort themselves across alternative states in the labor market. Second, we use Bayesian estimation and time-use data for actual couples from the German TUS to estimate our model. We thus create a rich lab which we use for various counterfactual exercises. Those exercises deliver insights into the quantitative importance of particular couple types to exogenous wage changes. By aggregating across individuals by gender we create a representative couple and link the implied wage-elasticity of total market hours worked by couples to the underlying cross-sectional distribution of those elasticities.

The closest paper to ours that considers the importance of heterogeneous couples' time allocation for aggregate variables is that by Attanasio et al. (2018) who study married couples in the U.S. Like us, they assume individual preferences to be non-separable in household consumption and individual leisure. Unlike us, they use a unitary life-cycle model of married couples with which they can quantify the intertemporal and intra-temporal margins of adjusting market hours and interactions of labor supply with the decision to save or consume. They assume that married men always work and focus on females' labor supply decisions. They use U.S. CEX data from 1980 through 2012 to estimate their model. When aggregating across couples they illustrate how the aggregate wage-elasticity of labor

differences in sectoral reallocations between European countries and the U.S., or Duernecker and Herrendorf (2018), and Ragan (2013). Borella, De Nardi, and Yang (2018) use a two-earners life-cycle model of the unitary type to study the quantitative importance of gender – in addition to that of the marital status – for replicating economic aggregates. Guner, Kaygusuz, and Ventura (2012) use the same setup to evaluate the effects that different reforms of the U.S. tax system have had on husband and wives' labor supply.

[7] See, for example, Blundell, Pistaferri, and Saporta-Eksten (2016).

[8] Household models where partners are assumed to play a cooperative game in which spouses settle on Pareto optimal outcomes are also known as collective models. They typically treat variations in the internal distribution of power as exogenous. Collective models were pioneered by Chiappori (1988), Apps and Rees (1988), and Browning and Chiappori (1998).

supply varies with the underlying type and degree of heterogeneity – including the distribution of reservation wages in the cross section. Their aggregation method — like ours — closely resembles that in Erosa, Fuster, and Kambourov (2016). Our study differs from theirs mainly in that we use a static setup, but allow for intra-household heterogeneity, in addition to inter-household heterogeneity, and also for males' labor supply to vary in reaction to their own wage rate and to that of their spouse.

3 The German Time-Use Survey

The German TUS is a quota sample survey of all private households in Germany that is designed and carried out by the Federal Statistical Office (Destatis)[9]. The quotation is based on the German microcensus. Excluded are homeless people and individuals living in group quarters or similar living institutions. Participating households enter voluntarily. Time-use surveys exist for three independent waves, namely 1991/92, 2001/02 and 2012/13. The first wave cannot be used, since it does not contain information on usual hours worked or on income which is necessary for estimating our model. The latter two waves comply with Eurostat's recommendations regarding the harmonization of time-budget surveys, and therefore are comparable with the content of the MTUS. For each wave, the reference period ranges from April of the earlier year to the end of March of the subsequent year in order to avoid seasonal distortions. The original data consist of three survey documents which we merge into our baseline dataset: information at the household level, each household member who is at least 10 years old provides socio-economic information about herself, and the same individual also keeps a diary over 24 hours on each of up to three days including both weekdays and weekends. These diaries contain activities in intervals of ten minutes. We use the 2001/02 wave for our analysis. We aggregate the individual records journalised in the diaries to daily measures of activities we need for our model estimation. Via the household dimension, we can identify couples and have detailed information about each spouse's time-use.

Our sample contains couples with partners each of whom is between 25 and 54 years old, that is in their prime working-age. We exclude from our sample couples with children below 6 years. Our model abstracts from children and also from time spent on childcare. Young children are known to impose a large tax on a couple's time-use and significantly affect partners' time-allocation. We plan to explore this topic in future research.[10]

Table 11 in the appendix reports the relative frequency of different types of couples in their prime working-age in the German TUS (using the appropriate representative weights) and contrasts them against the respective figures from the German microcensus.[11] The entries show that over 60 percent of all individuals in the indicated age-range live in couples, and that the vast majority of them are couples without children younger than six years. This group, which is the object of our study, is representative in the TUS compared to the microcensus. Couples with children younger

[9] See https://www.destatis.de/EN/FactsFigures/SocietyState/IncomeConsumptionLivingConditions/TimeUse/TimeUse.html for a detailed description of the data.

[10] There exist household models in which young children are captured as a public good that both partners can enjoy and to which they have to contribute goods or available time in order to foster them. See, e.g. Blundell, Chiappori, and Meghir (2005), or Doepke and Tertilt (2019).

[11] See https://www.forschungsdatenzentrum.de/en/household/microcensus

than six years are over-represented in the TUS, while persons living in other conditions than single or couples are under-represented.

We define and compute three categories of time use: market work, home production and leisure. In doing so, we follow Aguiar and Hurst (2007) as closely as possible and distinguish between a core activity and a more broadly defined activity. Core market work comprises time spent in the main or secondary job as well as training on the job. Total market work adds related activities such as searching for another job, taking breaks and commuting. We will use core market work in our estimation below. Core home production encompasses preparing meals and maintenance activities in the home. Total home production adds shopping, gardening, construction and childcare. These categories refer to the primary task that is carried out during the assigned time interval. Since we cannot separately measure care for elderly or handicapped in home production, we deviate from Aguiar and Hurst (2007) by including these activities in home production. We will use total home production in our estimation below. We compute daily leisure as a residual by subtracting six hours for sleep and personal care, core market work and total home production from 24 hours. We consider only regular working days in our sample.

We categorize the couples in our sample by each partner's labor market status: both partners work in the market, only the man works, only the woman works, and no partner works. Not working encompasses both the formal definitions of being unemployed and out-of-the-labor force. We discard unreasonable work hours per day, i.e., more than 14 hours of core market work and more than 16 hours of total market work, or less than two hours.

Apart from spouses' time-use, the German TUS provides information on each spouse's individual characteristics. It also allows us to infer individual hourly wage rates as well as the household's non-labor income. These variables are crucial for estimating our model. In order to obtain individual earnings, we construct the wage income from the main job. When only bracketed information is available, we use the mid-point of the bracket as an approximation for the earnings. We then compute the hourly wage rate by dividing wage income from the main job by usual hours worked. We discard unreasonably high hourly wages, i.e., wage rates above 200 Euros. We take total household income from the survey and compute the household's non-wage income as the difference between total household income and the sum of the individual wage incomes. All wages and income are net of taxes.

Our baseline sample encompasses 935 couples and a total of 3,142 observations. Table 1 shows the average daily time-use of couples according to their labor market status. When both partners work, women work less in the market and more at home compared to their partners, while both enjoy a similar amount of leisure. When only one partner works, the other works more at home and enjoys more leisure. However, if women are the sole wage-earner, they provide fewer market hours and more home production than men in case they are the sole earner. As is to be expected, childcare is negligible as a primary component of home production if kids are older than 6 years. The bottom of the table shows the average time-use of men and women in the sample. One may view this as a representative couple in case no further information about the actual partners' choice is available.

Table 12 in the appendix exhibits unweighted means, standard deviations, percentiles and min and max values of daily core market work, total home production and leisure by gender for the full sample and by couple type. The substantial heterogeneity in time use will be taken into

couple status	gender	market work		home production			leisure
		total	core	total	core	child	
EE	female	7.557	6.612	3.363	1.760	0.334	8.025
	male	9.262	7.958	1.924	0.590	0.162	8.118
EN	female	0.112	0	7.457	4.183	0.902	10.54
	male	9.226	7.950	1.715	0.477	0.250	8.335
NE	female	7.388	6.517	2.950	1.471	0.232	8.533
	male	0.0808	0	5.419	2.020	0.473	12.58
NN	female	0.118	0	6.187	3.445	0.337	11.81
	male	0.182	0	4.977	1.460	0.109	13.02
RC	female	5.109	4.441	4.610	2.496	0.482	8.950
	male	8.228	7.064	2.234	0.688	0.200	8.702

Table 1: Average daily time use 2001/2002. Figures show daily averages of time-use aggregates in hours. In home production, the sum of core and child is less than total home production, where child denotes childcare. Couple status refers to employment, E, or non-employment, N, of male and female partners. The representative couple (RC) shows the average time-use of males and females irrespective of their couple's labor market status. All numbers are averages using representative weights at the household level.

account in our model by allowing for heterogeneity in wage rates as well as preference parameters. Table 13 further documents correlations between these key time use variables. Market work is generally negatively related to home production and leisure for individuals. Own home production is weakly positively related to the partners market work, own leisure is weakly negatively related to the partners market work. Home production of partners within a couple are only very weakly positively related. Hourly wage rates of spouses are barely correlated (-0.0077) indicating little assortative mating by their respective productivity in our sample.

Table 14 in the appendix documents labor and non-labor income as well as age and educational degree of the couples in our sample sorted by their respective labor market status. Even for couples of the same labor market status the variation in wages and income is high. In our sample, dual-career couples make up the largest share. Women tend to earn substantially lower market wages than men. Also, couples with no partner working in the market or only the woman working have substantially higher non-labor income than others. Couples with no partner working tend to be somewhat older than other couples. Women are on average a few years younger than their male partner. Table 14 also reports the educational achievement of men and women by couples' labor market status. Men tend to be more highly educated than their female partners. Education is highest among dual-career couples.

Table 15 in the appendix shows the main source of income for couples according to their labor market status. For dual-career couples or those where only the male is working, the main source of income is wage income. The main source of non-wage income are pensions and unemployment benefits. In addition to the variables already mentioned we use information on whether or not a couple is married and whether they reside in the east or the west of Germany for our empirical work.

4 The Model

We model each couple as a pair of male m and female f who interact in the allocation of their available time and also in their goods consumption. The model is static. We take couples as given and consider neither their mating or marriage decisions nor their decisions to maintain the relationship or break up. Members of a couple gain from a partnership, because they can at least partially specialize in the type of goods production in which they have a comparative advantage and subsequently consume more goods than if they remained single.[12]

First, we describe the economic environment. Then we characterize the solution under the *non-cooperative Nash equilibrium*, in which members of couples optimize taking the strategy of the other party as given.[13]

4.1 The economic environment

The economy consists of couples, comprised of two individuals, which we label *male* and *female* for notational convenience. We index couples with $j \in \mathcal{C}$, but suppress this in this section as our analysis is partial equilibrium, and thus we always focus on the decision problem of a given couple. Each individual $i \in \{m, f\}$ in a couple can allocate his or her available time T_i between market work, n_i, home work h_i, and leisure ℓ_i; thus facing the time constraint:

$$\ell_i + h_i + n_i \leq T_i. \tag{1}$$

Individual consumption comprises goods that are either purchased in the market, c, or domestically produced, z, using home work as sole input. Due to the lack of available data on consumption expenditures and home-produced goods, we assume both types of consumption to be public goods. Each partner can voluntarily contribute to the "production" of these goods. Bought-in consumption goods are purchased using total non-labor income M plus total earnings $w_m n_m + w_f n_f$, where w_i denotes the net hourly real wage rate of individual i. Hence, we assume partners in a household to pool their income, since we have information on individual earnings if employed, but not on the individual share of non-labor income. The household faces the budget constraint

$$c \leq M + w_m n_m + w_f n_f, \tag{2}$$

where $w_i n_i$ denotes the wage income of each individual. Given that our approach is static, we model M, w_m, and w_f as exogenous.

Without loss of generality, we normalize the price of the bought-in good to unity. The nonmarket good z is nontradable, and its production is captured by a Cobb-Douglas home production function:

$$z(h_m, h_f) = h_m^{\gamma_m} h_f^{\gamma_f}, \tag{3}$$

[12] They may also gain from economizing on household maintenance costs, but we do not explicitly model them.

[13] A table summarizing notation is available in Appendix B.

where

$$\gamma_m + \gamma_f = 1 \qquad \text{and} \qquad 0 \leq \gamma_m, \gamma_f \leq 1$$

are effectively a single parameter that characterizes the home production function; however, for symmetry of the formulas it is convenient to use both γ_m and $\gamma_f = 1 - \gamma_m$. This particular function treats male and female time in home production as partially substitutable. Consistent with the empirical evidence on actual time use of couples it ensures that in equilibrium, each spouse contributes some positive amount of homework.

Individual preferences are defined over a market consumption good, a non-market consumption good, and leisure. They are captured by a Cobb-Douglas utility function that is continuous, linear homogeneous and strictly concave. The parameter α_i denotes individual i's utility weight on market consumption, and $1 - \alpha_i$ captures the weight on non-market consumption and leisure, which are aggregated using a Cobb-Douglas form with weights β_i and $1 - \beta_i$ on the nonmarket good and leisure, respectively. Consequently, we model each individual's utility as

$$U(c, z, \ell_i) = c^{\alpha_i} \left(z^{\beta_i} \ell_i^{1-\beta_i} \right)^{1-\alpha_i} \qquad \text{for } i = m, f \tag{4}$$

4.2 Non-cooperative equilibrium

Assume that the partners forming a household interact non-cooperatively in that each of them individually maximizes utility while taking their partner's decisions as given. Hence, each member $i \in \{m, f\}$ of a couple solves the following decision problem:

$$\max_{n_i, h_i, l_i} U(c, z, \ell_i)$$

subject to her individual time constraint (1), the budget constraint (2), the home production function (3), and several non-negativity constraints:

$$c, z, \ell_i, h_i > 0, n_i \geq 0.$$

In order to simplify the analysis, it is convenient to introduce the notation k for the *other* individual of the couple: that is to say, when $i = m$ then $k = f$, and *vice versa.*

Thus, each member i of the household takes the leisure, home production, and market hours choices ℓ_k, h_k, n_k of the other member k as given. Reaction functions would then provide two mappings

$$(\ell_m, h_m, n_m) \mapsto (\ell_f, h_f, n_f)$$
$$(\ell_f, h_f, n_f) \mapsto (\ell_m, h_m, n_m),$$

the fixed point of which would be the equilibrium. However, since the utility function (4) is *separable* in market hours n_i and the joint leisure-home production choice (ℓ_i, h_i), we can solve our problem in two steps:

1. Holding n_m and n_f fixed, we derive the optimal choices of (ℓ_i, h_i), $i = m, f$, and the indirect utility functions $\hat{U}_i(n_m, n_f)$, $i = m, f$.

2. Using the indirect utility functions $\hat{U}_i$, we derive the reaction functions

$$\begin{aligned} n_m &\mapsto n_f \\ n_f &\mapsto n_m \end{aligned}$$

and find their fixed point, which yields the equilibrium.

Consequently, we first fix n_m and n_f, and maximize (4), substituting in the functional form (3). Note that the consumption term is separable, so the problem simplifies to

$$\begin{aligned} &\max_{h_m, \ell_m} h_f^{\beta_m \gamma_f} h_m^{\beta_m \gamma_m} \ell_m^{1-\beta_m} \\ &\max_{h_f, \ell_f} h_f^{\beta_f \gamma_f} h_m^{\beta_f \gamma_m} \ell_f^{1-\beta_f}, \end{aligned}$$

which can be written compactly as

$$\max_{h_i, \ell_i} h_k^{\beta_i \gamma_k} h_i^{\beta_i \gamma_i} \ell_i^{1-\beta_i}. \qquad \text{for } i = m, f$$

The first order conditions characterizing our equilibrium are

$$\begin{aligned} \frac{\ell_i}{T_i - n_i} &= \frac{1-\beta_i}{1-\beta_i+\beta_i\gamma_i} \equiv \nu_i \\ \frac{h_i}{T_i - n_i} &= \frac{\beta_i\gamma_i}{1-\beta_i+\beta_i\gamma_i} \equiv 1-\nu_i. \end{aligned} \tag{5}$$

Consequently,

$$z = h_m^{\gamma_m} h_f^{\gamma_f} = \text{constant} \cdot (T_m - n_m)^{\gamma_m} (T_f - n_f)^{\gamma_f}$$

and, therefore, the Nash equilibrium can be characterized by solving

$$n_i^* = \underset{0 \le n_i \le T_i}{\text{argmax}}\, c^{\alpha_i} \left((T_i - n_i)^{1-\beta_i+\beta_i\gamma_i} (T_k - n_k)^{\beta_i \gamma_k} \right)^{1-\alpha_k} \text{ given } n_k = n_k^*, \text{ for } i = m, f.$$

Using (2) and ignoring quantities which are constant from the point of view of each member of the couple, these problems can be transformed to

$$n_i^* = \underset{0 \le n_i \le T_i}{\text{argmax}} (M + w_i n_i + w_k n_k)(T_i - n_i)^{\phi_i} \qquad \text{given } n_k = n_k^*, \text{ for } i = m, f, \tag{6}$$

where we have defined

$$\phi_i = \frac{1-\alpha_i}{\alpha_i}(1-\beta_i+\beta_i\gamma_i) \tag{7}$$

to simplify notation.

4.3 Equilibrium regions

In Appendix C we show that the solution of the optimization problem in (6) can be characterized as

$$w_i n_i = \frac{(T_i w_i - \phi_i(M + w_k n_k))^+}{1+\phi_i} \qquad \text{for } i = m,f, \tag{8}$$

where ϕ_i, M, w_i, T_i are given for $i=m,f$, and we are looking for the n_i for $i=m,f$ that solves (8). We refer to $n_i w_i$ as *earnings* of the individual. We solve (8) for $n_i w_i$ for $i=m,f$ by considering the four possible cases, providing the complete characterization in the lemma below. Having solved for $n_i w_i$, we can then recover individual market hours n_i.[14]

Lemma 1. *The system* (8) *always has a unique solution* $n_i w_i, n_k w_k$*, which depends on* $M, T_i w_i, T_k w_k$ *as follows.*

(NN) *When*

$$T_i w_i \le \phi_i M, \qquad \textit{for } i = m,f,$$

the solution is

$$n_i w_i = 0, \qquad \textit{for } i = m,f. \tag{9}$$

(EN,NE) *When for* $i=m,f$ *(note that this covers two cases),*

$$T_i w_i > \phi_i M, \quad T_k w_k \le \frac{\phi_k}{1+\phi_i}(M + T_i w_i), \tag{10}$$

the solution is

$$n_i w_i = \frac{T_i w_i - \phi_i M}{1+\phi_i}, \quad n_k w_k = 0. \tag{11}$$

(EE) *Finally, when*

$$T_i w_i > \frac{\phi_i}{1+\phi_k}(M + T_k w_k), \quad \textit{for } i = m,f,$$

the solution is

$$n_i w_i = \frac{T_i w_i (1+\phi_k) - \phi_i (M + T_k w_k)}{1+\phi_i+\phi_k}, \quad \textit{for } i = m,f. \tag{12}$$

Also, the four cases above form a partition of $\mathbb{R}^2_+$.

Proof. Guess and verify. □

We use the abbreviations EE, EN, NE, and NN for the region the couple is in. The first and the second letter represent the male's and the female's employment status, respectively. They can be employed, E, or non-employed, N.

Illustrating Lemma 1, Figure 1 shows the four regions for the solution in work hours n_i. When

$$w_i \le \phi_i \cdot \frac{M}{T_i} \qquad \text{for } i = m,f,$$

[14] Without loss of generality, we characterize $w_i > 0$ for $i=m,f$. When $w_i \le 0$, trivially $n_i = 0$.

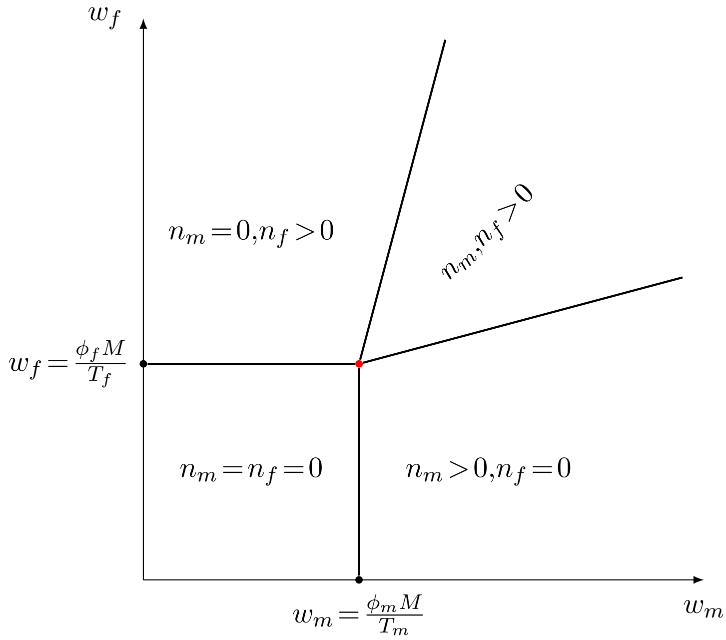

Figure 1: The four regions for work choices (see Lemma 1 and the subsequent discussion).

neither member of the couple works, since their wage is too low compared to their other income. In this case, the above expression corresponds to their reservation wage. However, when person k in the couple works, this raises the reservation wage for i according to

$$n_i > 0 \qquad \Leftrightarrow \qquad w_i > \phi_i \cdot \frac{M + n_k w_k}{T_i}$$

Our derivations reflect Gourio and Noual (2009) who stress that the reservation wage can be viewed as a sufficient statistic onto which the different dimensions of heterogeneity such as tastes and non-labor income have been projected and which is essential for the labor supply choice.

For a given reservation wage, a change in person i's wage offer moves this person's market hours within and across regions, i.e., labor market states in Figure 1. Intuitively, since the couple's earnings are shared, the spouse's earnings are treated as an addition to other non-wage income. Hence, the spouse's wage w_k increases the reservation wages and *ceteris paribus* leads to a fall in market hours for a given wage offer. Also note that person i's reservation wage depends on ϕ_i which decreases both in α_i or β_i.[15] That is, a rise in either α_i or β_i lets the reservation wage decrease and *ceteris paribus* leads to a rise in market hours for a given wage offer. This is intuitive: with a rise in α_i individual *i* values market consumption more and is willing to provide more market hours. A rise in β_i lets individual *i* substitute leisure time by housework and also by market work. Such a shift in the individual preference parameters can graphically be depicted as shifting the separating contours of the four equilibrium regions in Figure 1 to the left, or to the bottom, respectively.

[15] Compare Equation (7) and note that $0 \leq \gamma_i \leq 1$.

4.4 Comparative statics

Our model of spousal time-allocation makes predictions about various wage-elasticities and how they react to variations in selected model parameters. In particular, it predicts the sign and the determinants of each individual's own-wage and cross-wage elasticity of market hours and how these elasticities change in reaction to wage-rates and preference parameters. These predictions will be useful for interpreting our estimation results and for building intuition about the forces at work. Below we formally derive expressions for an individual's own-wage and cross-wage elasticity of market hours worked. We also investigate how these elasticities vary in an individual's own wage-rate and preference parameters as well as in those of her partner. The following expressions relate to market hours' adjustment along the intensive margin.

First, we derive the own-wage elasticity of market hours for dual-career couples (EE) in equilibrium based on Equation (12)

$$\epsilon_{w_i}^{n_i} \equiv \frac{\partial n_i}{\partial w_i}\frac{n_i}{w_i} = \frac{\phi_i(M+T_k w_k)}{(1+\phi_k T_i w_i)-\phi_i(M+T_k w_k)}. \tag{13}$$

This expression is unambiguously positive, i.e., a person increases hours worked when his or her wage increases and the corresponding own-wage elasticity is positive. As can be seen directly from Equation (13), the own wage elasticity decreases in the own wage. The own wage elasticity also decreases in α_i and β_i. This is also true if person i works and his or her partner does not (compare Equation (11)). If person i does not work, his or her elasticity is zero (compare Equations (11) and (9)). If both partners work, the own wage elasticity reacts positively to a change in the partner's parameters, but not otherwise.

Second, we derive the corresponding cross-wage elasticity of market hours

$$\epsilon_{w_k}^{n_i} \equiv \frac{\partial n_i}{\partial w_k}\frac{n_i}{w_k} = -\frac{\phi_i T_k w_k}{(1+\phi_k T_i w_i)-\phi_i(M+T_k w_k)}.$$

This expression is unambiguously negative, i.e., a person decreases hours worked when his or her partners wage increases and the corresponding cross-wage elasticity is negative. It reacts positively to a change in one's own wage rate and in own preference parameters, but negatively to a change in the partner's parameters. Cross-wage elasticities only apply for couples that are or become dual-earner couples due to a change in labor market status of the partner.

5 Estimation

We use Bayesian methods to estimate the model. Specifically, we obtain posterior distributions for the common cross-sectional parameters and *individual-specific* αs, βs, and wages (for the non-employed). In the context of our model, this is also advantageous since employment and hours are *nonlinear* transformations of individual-specific parameters. When we calculate elasticities and counterfactuals in Section 6, the availability of a posterior sample allows us to compute counterfactuals on each posterior sample draw sample (eg increase wages by 10%), and then calculate employment and hours. Constructed this way, our results take the nonlinearity of the model into account.[16]

We use a *multilevel model* with weakly informative priors for the cross-sectional parameters. Multilevel methods automatically pool cross-sectional information and are a natural fit for the hierarchical nature of our data. They also allow us to estimate a conditional distribution of unobserved wages (for the non-employed) relying only on *a priori* exchangability of individual-specific error terms.[17] Specifically, our model has the following hierarchical layers: First, individual-specific parameters are assumed to be drawn *ex ante* from a common distribution. Second, given the parameters for each couple, we allow the allocation implied by the model to be observed with a noise, allowing for the daily variation in time use patterns we observe in the data.

Section 5.1 describes our choices for multilevel and noise distributions, while Section 5.2 briefly summarizes the priors. Section 5.3 introduces the domain transformations which are essential for effective sampling, and form a key part of our estimation methodology.[18]

5.1 Cross-sectional and noise distributions

The equilibrium that we have discussed in Section 4 provides a mapping from the other income M, wages w_i, preference parameters α_i, β_i for $i = m, f$, and technology parameter γ to choices of market, leisure, and home production hours:

$$(M, w_m, w_f, \alpha_m, \alpha_f, \beta_m, \beta_f, \gamma) \mapsto (n_m, n_f, \ell_m, \ell_f, h_m, h_f) \tag{14}$$

First, note that while (7) identifies αs, βs and γ are not separately identifiable at the individual level. That is to say, for every ϕ_m, ϕ_f in (7), there are multiple β_m, β_f, γ that lead to the same allocation.[19] We thus fix γ at 0.5. In Section 6.6, we address robustness to our results when varying γ to 0.3 and 0.7.

There are two additional ingredients that are necessary to complete the specification of the data generating process of the model: the specification of a cross-sectional model for the distribution of parameters, and a mapping from hours predicted by the model in (14) to the hours observed in the data that are necessarily noisy by construction. We consider each of these in turn.

We also need to assume a functional form for the *ex ante* cross-sectional distribution of wages, and preference parameters. Since we would like to avoid overfitting the model, it is important to choose a simple functional form, but at the same time we would like to avoid ruling out possible *correlations* between preferences and wages, either for the same individual (e.g. between α_i, β_i, and w_i), or between spouses.[20] In order to strike a reasonable balance between these two requirements,

[16] In contrast, statistical methods that obtain point estimates may grossly over- or underestimate the couple-specific probability of switching employment status depending on where the point estimate falls. We explain this further in Section 6.3. Methods that use approximations around a mode may do slightly better, but have no theorerical guarantees for predictive accuracy when variable transformations are not continuously differentiable.

[17] For recent introductions to multilevel models, we recommend Gelman and Hill (2007), Snijders and Bosker (2011), and Hox, Moerbeek, and Schoot (2017). The importance of exchangeability in hierarchical models is discussed in Bernardo (1996).

[18] Convergence statistics of MCMC are available in Appendix D. We check our model assumptions with posterior predictive checks in Appendix E.

[19] Conditional on a concrete distribution in (15), γ would be *weakly* identifiable in the statistical sense. However, we do not pursue this since the normal distribution was chosen for convenience.

[20] Section 6.3 explains why this is important when we calculate responses of hours.

we use distributions of the form

$$\begin{bmatrix} \text{logit}^{-1}(\alpha_m) \\ \text{logit}^{-1}(\beta_m) \\ \log(w_m) \\ \text{logit}^{-1}(\alpha_f) \\ \text{logit}^{-1}(\beta_f) \\ \log(w_f) \end{bmatrix} \sim \text{Normal}(BX,\Sigma), \qquad \text{IID}, \tag{15}$$

where X is a matrix that contains individual-specific covariates (such as gender and age) for members of the couple, augmented by a constant to capture the level, and B is a coefficient matrix. The parameters (B,Σ) characterize this distribution family.

This transformed distribution family is flexible, yet at the same time simple to parameterize and has parameters which are easy to interpret intuitively. For example, if Σ is close to being diagonal, then there would be no correlation between the model parameters and wages, while a block-diagonal structure would demonstrate correlation for individuals (e.g. between α_i and w_i), but no correlation between spouses. Deviations from this allow us to model assortative matching between couples.

It is important to emphasize that (15) is IID *ex ante*, but conditional on the actual realizations of hours, individuals and couples will of course be different *ex post* — for example, a couple where both members are working will probably have higher wages or α's compared to a couple where both members are non-employed. This is especially important for wages, which we observe directly only for the employed individuals. When analyzing the results, we are careful about distinguishing *ex ante* wages, which are realizations from the distribution (15) and may or may not be observable, and *observed* wages, which are wages for the employed individuals.

As discussed in Section 3, time use information is collected in 10-minute blocks, while the model delivers a nonnegative real number below the total time endowment T_i for each member of the couple. Moreover, when looking at the data, we find that couples for which we have data from multiple days do not generally choose the same time allocation for each day in the data. In order to allow for this, we introduce noise distributions

$$\frac{n_{j,i,\text{observed}} - n_{j,i,\text{model}}}{T_i} \sim N(0,\sigma_\eta^2)$$
$$\nu_{j,i,\text{observed}} - \nu_{j,i,\text{model}} \sim N(0,\sigma_\nu^2),$$

which are IID across couples $j \in \mathcal{C}$ and for $i = m,f$. This ensures that the expected values are preserved.

5.2 Priors

Following standard Bayesian practice, we use weakly informative prior distributions,[21] which we describe briefly. We choose an IID $N(0,5)$ prior for the elements of B, and model the covariance

[21] See Gelman (2004).

matrix Σ as marginal variances σ and correlation Ω, i.e.

$$\Sigma = \operatorname{diag}(\sigma_\Sigma) \cdot \Omega \cdot \operatorname{diag}(\sigma_\Sigma),$$

where Ω is a correlation matrix. This matrix is hence positive definite with a unit diagonal, and the elements of σ are standard deviations, and thus positive. For the covariance matrix, we use the construction algorithm of Lewandowski, Kurowicka, and Joe (2009) to generate a Cholesky factor of Ω, then use the prior

$$p(\Omega \mid \eta_\Omega) \propto \det(\Omega)^{\eta_\Omega - 1}$$

with $\eta_\Omega = 2$, which ensures a vague but unimodal prior. For the elements of σ_Σ, we follow Polson, Scott, et al. (2012) and use the half-t prior with 7 degrees of freedom, which is also vague but sufficient to make the posterior proper. Finally, we use $\sigma_\eta, \sigma_\nu \sim N(0,1)$ truncated above 0 for the noise parameters.

5.3 Domain transformations

We implement our model in Stan,[22] using the NUTS algorithm of Hoffman and Gelman (2014). As usual in Bayesian analysis, many of our parameters are *constrained*, while the NUTS algorithm is designed to very efficiently sample from an *unconstrained* posterior defined on $\mathbb{R}^n$. We need an efficient sampler in high dimensions since unknown parameters for each couple (preferences, and for the non-employed also wages) are treated as parameters to be estimated, so the dimension of the parameter domain is above 6,000.

This requires transformations to the valid parameter domain from $\mathbb{R}^n$. Most of these transformations are standard (eg from $\mathbb{R}$ to $\mathbb{R}^+$ for a standard deviation), to the extent that commonly used software implements them, automatically adjusting the log posterior by the log determinant of the Jacobian of the transformation. However, efficient sampling of the posterior using algorithms from the NUTS/HMC family requires that we implement some transformations specific to the model used in this paper.

Consider, for example, a couple which has both members employed in the data (type EE). For this couple, wages w_m, w_f and the other income M are known, and the preference parameters α_i, β_i for $i = m, f$ are naturally constrained to lie between 0 and 1. From Lemma 1, we know that only a *subset*

$$T_m w_m > \frac{\phi_m}{1+\phi_f}(M + T_f w_f)$$
$$T_f w_f > \frac{\phi_f}{1+\phi_m}(M + T_m w_m)$$

of this region (where ϕs depend on αs and βs) would yield an allocation which would make both members employed.[23] Unless we efficiently constrain to this subset, the posterior sampler will

[22] Stan Development Team (2020).

[23] In this derivation, we treat $T_i w_i$ as a single variable, effectively as a daily wage. This merely simplifies the algebra, and does not change the results, as transforming to w_i from $T_i w_i$ is a linear transformation and has a fixed log Jacobian

visit regions which are not compatible with the data at all (i.e. have 0 probability). This may seem unimportant when we are talking about *one* couple, but considering the whole parameter space which is a cross-product of *all individual-specific parameters*, it is easy to see that the volume of the feasible parameter region *given the employment status* will be very small compared to *ex ante* domain which is a cross-product of $[0,1]$ intervals.

Conditional on the data (employment status, wages, other income), we introduce the following transformation. Let $0 \leq \mu_m, \mu_f \leq 1$ be parameters to be estimated, and rewrite the equations above as

$$T_m w_m \mu_m = \frac{\phi_m}{1+\phi_f}(M + T_f w_f)$$
$$T_f w_f \mu_f = \frac{\phi_f}{1+\phi_m}(M + T_m w_m).$$

We solve this for the ϕs. Introduce

$$A_i = T_i w_i \mu_i \text{ for } i = m, f \quad \text{and} \quad D = (T_m w_m + M)(T_f w_f + M) - A_m A_f$$

and obtain

$$\phi_m = A_m \frac{A_f + T_m w_m + M}{D}$$
$$\phi_f = A_f \frac{A_m + T_f w_f + M}{D}.$$

This mapping $(\mu_m, \mu_f) \mapsto (\phi_m, \phi_f)$ can be shown to have a log Jacobian determinant

$$\log(\det(J)) = \log(T_m w_m) + \log(T_f w_f) + \log(1+\phi_m) + \log(1+\phi_f) - \log(D).$$

Then, for each couple, we solve (7) for α_m, α_f as a function of β_m, β_f and similarly adjust the log posterior with the corresponding log Jacobian determinant.

For EE couples, this effectively yields a bijection from $(\mu_m, \mu_f, \beta_m, \beta_f) \in [0,1]^4$ to the domain that is compatible with their employment outcome according to Lemma 1. Using the common $\mathbb{R} \to [0,1]$ logistic transformation, we can effectively sample from the constrained posterior.

Similar transformations using the system of relevant inequalities can be derived for the EN, NE and NN couples from the constraints of Lemma 1. Whenever a member of a couple is non-employed, we use $\lambda_i > 1$ for that person (since the inequality goes in the other direction), and also include the wage as a parameter to be estimated.

It is important to emphasize that these transformations are *data-dependent*, since the parameter region compatible with particular employment outcomes depends on wages w_m, w_f (if applicable) and non-wage income M. Each couple needs an individual, parameterized transformation for each evaluation of the posterior.

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determinant, which can be ignored. Recall that the ϕs are defined in (7).

6 Results

We discuss estimated parameters in subsection 6.1, then illustrate identification in subsection 6.2. Then we proceed to counterfactual experiments, calculating elasticities in section 6.3, then quantify and decompose aggregation bias in sections 6.4 and 6.5.

6.1 Estimated parameters and distributions

The posterior estimates of the parameters α and β and also of the wage rates in the B matrix are depicted in Figure 2. Blue dots correspond to the point estimates for males, and red dots to the ones for females. The horizontal bars represent posterior quantiles with the thick bars corresponding to the 25%–75% quantile and the thin ones to the 5%–95% quantile. Each panel depicts for males and females the direction and extent by which any of the explanatory variables affects the particular parameter considered. For example, the upper left panel indicates that α tends to decline for men and women in all explanatory variables except for females who are married or hold a secondary school degree. Moreover, the decline in α is progressive in age. Remarkably, these estimates are by and large mirrored in the lower panel which reports the reaction of male and female wage rates to the explanatory variables. Wages regressively rise in age, and they rise for men and women in all other variables except for when women are married or have children. To check the plausibility of these results, we use OLS and estimate Mincer-type wage regressions for men and women with the same explanatory variables as in the Bayesian estimation. The point estimates are represented by a small cross. When contrasting the wage estimates from these two procedures, we conclude that the posterior wage estimates are consistent with the OLS estimates and plausible.[24]

Figure 3 depicts cross-sectional marginal posterior densities for spouses' estimated model parameters by couples' labor market state. In each panel, the dotted vertical line depicts the parameter value corresponding to the members of the representative couple. Two observations stand out. First, the shape of each marginal density is primarily determined by dual-career couples (EE) and traditional couples (EN). Second, for dual-career couples the marginal distributions of wage rates are right-skewed, whereas the ones for the α parameters are left-skewed. These observations will matter for the aggregation exercise in Section 6.5.

6.2 Illustration of identification

We discuss the intuition for identification of individual-specific parameters, using the results for a specific EN couple as illustration.[25] The data for this couple is shown in Table 2. Note that for this particular EN couple, we have two weekdays of observations, the variation of which is fairly typical for our data.

As is standard in multilevel models, the distribution parameters α_i,β_i for each individual, and for the non-employed also w_i are *jointly* identified conditional on the data and the hyperparameters.

[24]Posterior quantiles for noise parameters are in Table 17 of Appendix F.

[25]We chose an EN couple because it demonstrates identification for both an employed and a non-employed member, EE and NN couples work analogously, *mutatis mutandis*. All other parts of the model are standard, with straightforward identification. See Appendix D for posterior-prior comparisons of common parameters.

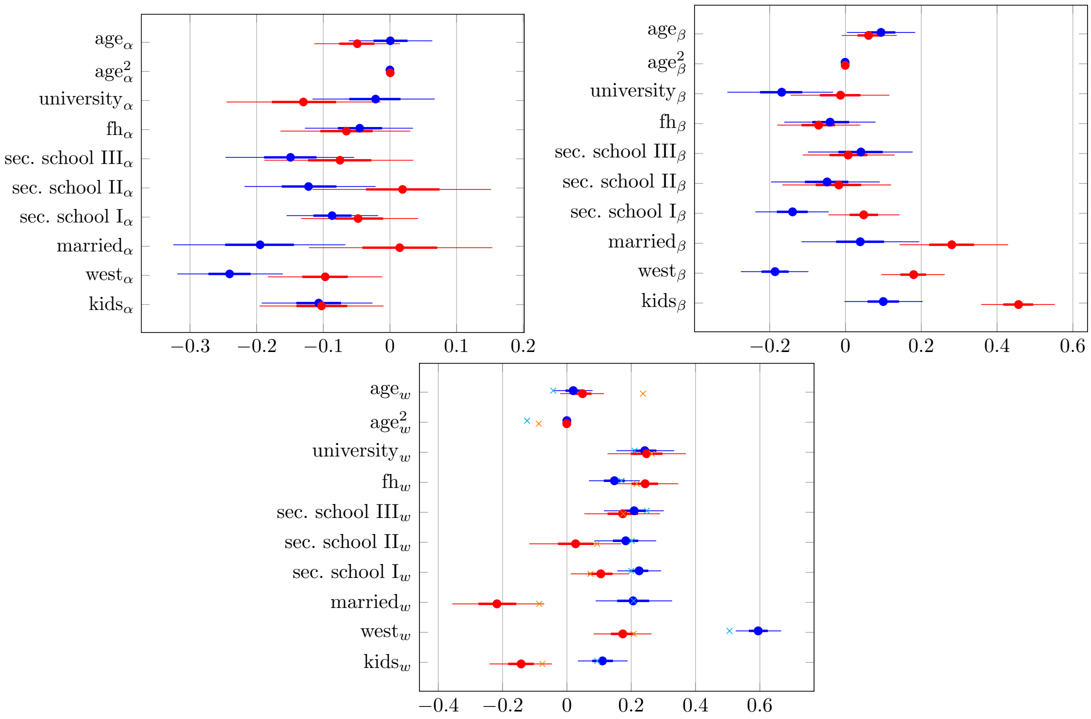

Figure 2: Posterior estimates for the B matrix. ▬ male, ▬ female. For the wage coefficients, × show OLS estimates on the subset of employed, by gender.

	w_m	n_m	ℓ_m	h_m	ℓ_f	h_f
day 1	10.18	7.00	6.50	4.50	6.00	12.00
day 2		8.33	4.33	5.33	7.33	10.66

Table 2: Data for a selected EN couple used to illustrate identification (time use as hours).

That is to say, conditional on noise magnitudes σ_ν, σ_η, hyperparameters σ_Σ, Ω, and B, the model assigns a posterior to *feasible* parameter regions according to Lemma 1 conditional on observed employment status and hours.[26]

Let's pretend that there is no noise, and use the *average* values across the two days. Let's also assume that we don't have a multilevel model. Since the mapping from the couple parameters to the hours is available, we could use (5) to calculate β_m and β_f. Given w_m and market hours, α_m would follow from (11) and (7), while for the female member we could calculate a feasible region (α_f, w_f) from (10).[27] The results are depicted in red in Figure 4, we refer to this as the "deterministic" identification. Importantly, for the employed member this results in a point estimate of the unknown parameters α_m and β_m, while for the non-employed spouse we have a point estimate of β_f and a feasible locus for (α_f, w_f). This is all that we would know without cross-sectional information that is incorporated via the hyperparameters.

In our model with noise and a multilevel structure, a posterior probability is calculated for *all feasible* values according to Lemma 1. Namely, for each $(\alpha_m, \beta_m, \alpha_f, \beta_f, w_f)$ that is compatible with

[26] The mechanics of the estimation that enforces this is described in Section 5.3.

[27] This mapping is similar to what has been derived by Del Boca and Flinn (2012), section 4.2.1

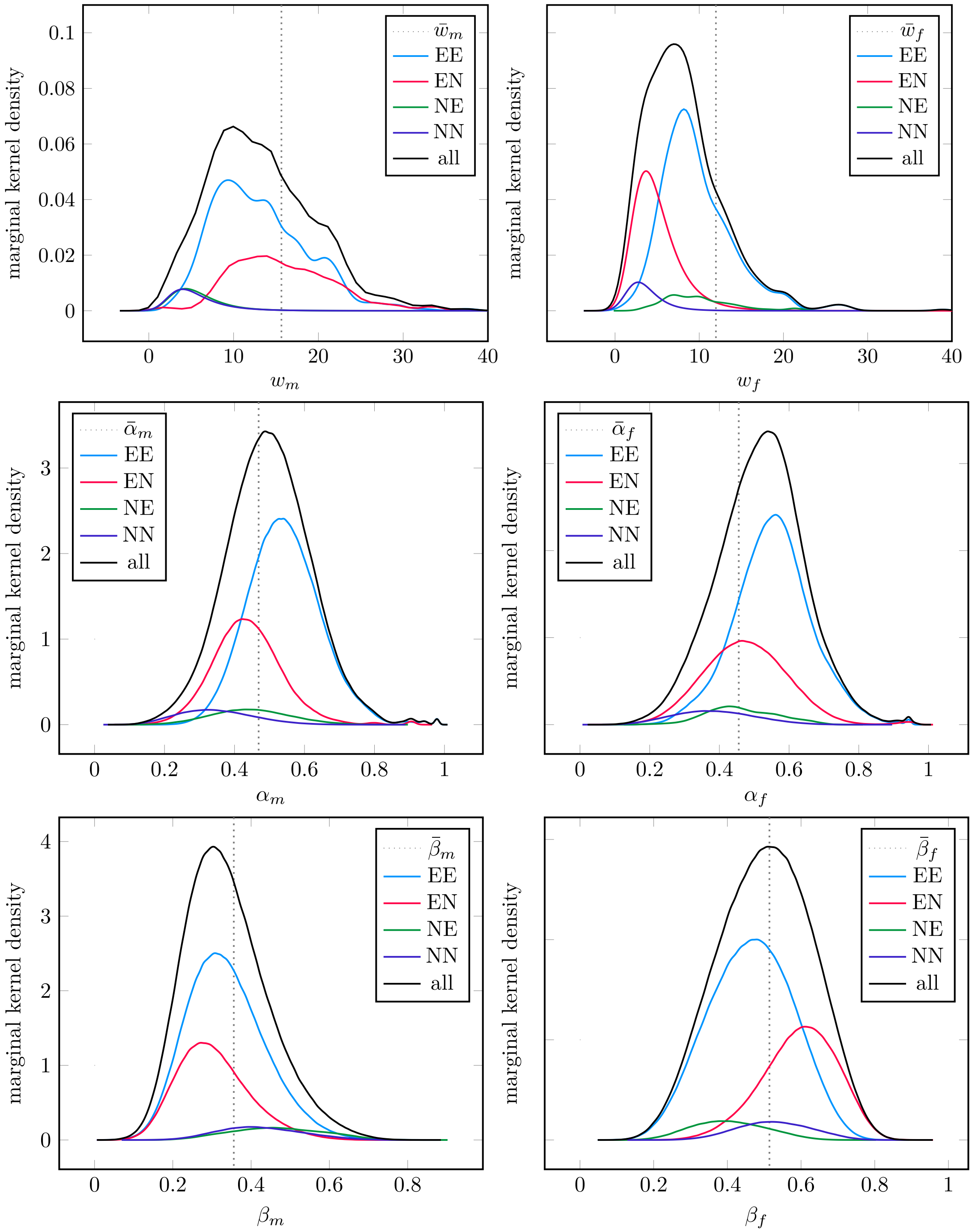

Figure 3: Cross-sectional marginal posterior densities.

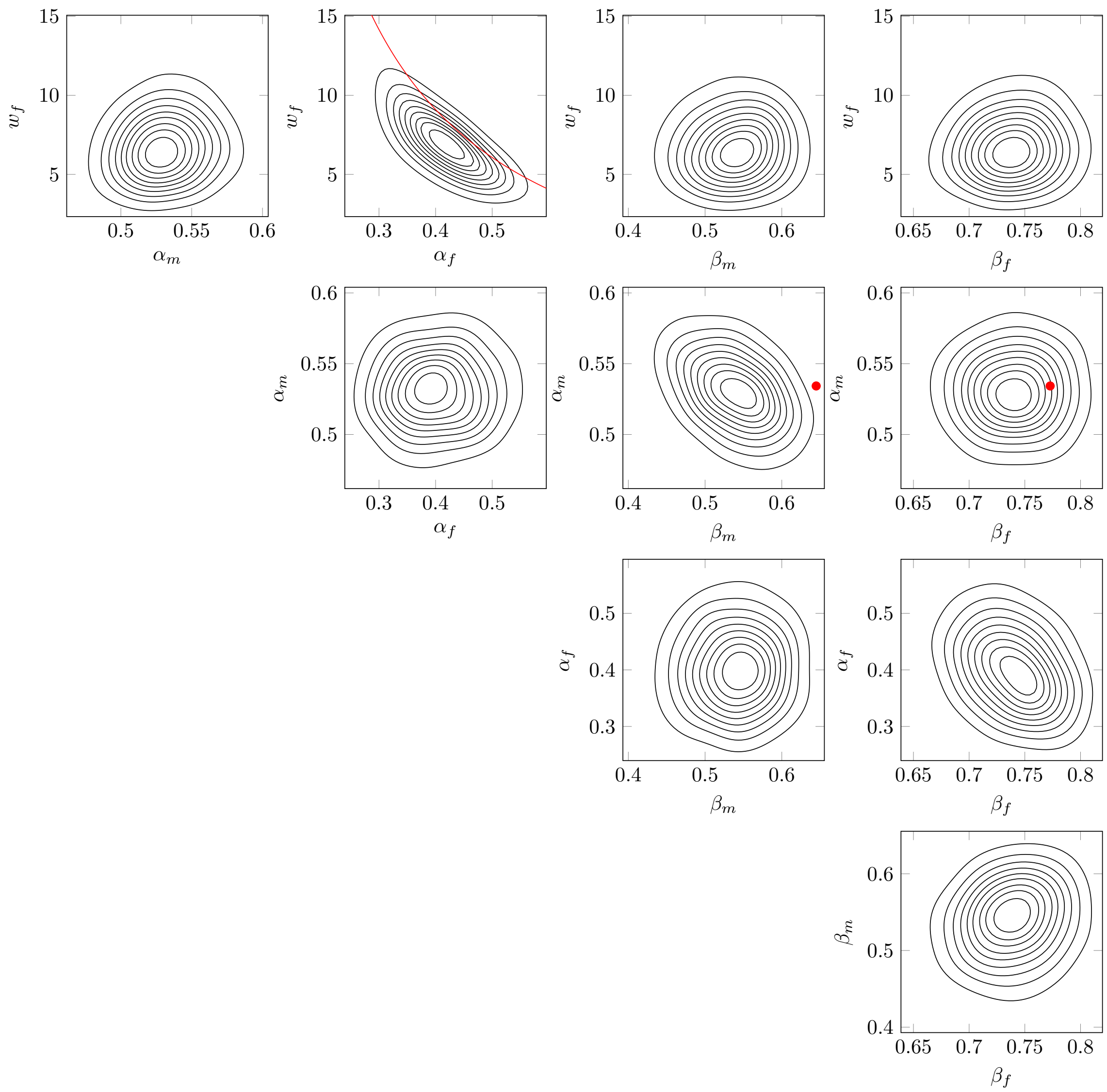

Figure 4: Posterior plots of individual-specific parameters for a selected EN couple. Black lines (—): 10%,...,90% HPD regions, red: deterministic identification, the feasible (α_f, w_f) region is below the red line (—) in the corresponding plot, red dots (●) show deterministically calculated values. Only a subset of plots are annotated with the latter, to avoid visual clutter.

an EN outcome, we can calculate posterior probabilities. This of course includes values which are not very likely — e.g. a β_f distant from what the hours choice would imply — but merely feasible. Corresponding highest posterior density (HPD) regions are illustrated in the same Figure 4, and allow us to highlight a couple of important points. First, note that there is considerable uncertainty about all parameters, which is a natural consequence of having a noise term in the hours observation, which is in turn required for modeling the actual variation in day-to-day allocations. Working with posteriors, all of our subsequent calculations take this into account by construction. Second, both the "deterministic" identification and the full identification enforce restriction (10) (with (7)). But only the full identification tells us where the probable values are. Third, note the difference between the "de-

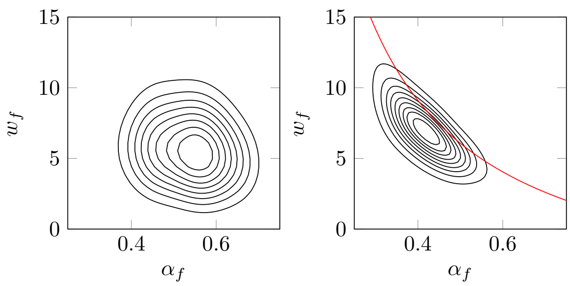

Figure 5: Comparison of posterior distributions not conditional (left) and conditional (right) on the data for a selected EN couple. Contour lines for highest posterior density regions at 10%,…,90%.

terministic" values and the posterior modes: for α_m and β_f it is minor, but for this particular couple β_m differs by about 0.1. This happens because the posterior pools information from the hyperparameters, which were estimated using the whole sample, including the observations for this specific couple. Intuitively, hyperparameters condense information from *other* couples, which is in turn applied to sharpen estimates for each particular couple, conditioning on employment status and hours.

For this specific couple, the information pooled from other couples can be considered a prior, which is then combined with the data from actual time use observations. The significant influence of the hyperparameters here reflects the fact that the regression in (15) turns out to be a good predictor of couples' wages and parameters, so in the combination of the hyperparameters and the couple-specific observation the former have a large weight.[28] Compared to similar couples in the whole sample, the observations of a particular couple may then be considered large or small, which explains this deviation. These deviations of course balance on average for the whole sample.

We illustrate how the hyperparameters and the couple-specific allocation data combine to form the posterior in Figure 5. The left panel shows the distribution of α_f and w_f generated from (15) using only posterior estimates for B and Σ and individual-specific covariates corresponding to this couple, but no information on time allocation. Importantly, these values incorporate what we learn about parameters B and Σ from all couples, but *ignore the information about the hours allocation and employment status of this particular couple.* That is then added in the right panel of the same figure, which corresponds to the relevant panel of Figure 4. Notice how allocation information sharpens the estimate for both parameters.

6.3 Cross-sectional elasticity estimates

In this section we use the estimated model as a laboratory to perform counterfactual experiments. To do this, let

$$\theta = (\alpha_m, \alpha_f, \beta_m, \beta_f, w_m, w_f)$$

denote the set of parameters that determine allocations in a couple and $F(\theta)$ the corresponding distribution. For employed persons, wages are known and there exist posterior draws for the other

[28] If we had a simple linear model with normal errors and no correlations for parameters, posterior modes for the couple-specific parameters would be weighted averages of the mean "deterministic" values and the linear prediction from (15), with the weights proportional to diagonal of Σ^{-1} and σ_ν^{-2} or σ_η^{-2}, as described in Gelman et al. (2013, p 116). Our setup is nonlinear and more complicated, but has the same intuition.

parameters, while for the non-employed all parameters are posterior draws. Hours worked of males and females depend on θ in a deterministic way, i.e. $n(\theta)$. We apply three *counterfactual* experiments C to these parameters on an individual level: increasing the offered or actual wage rate of males by 10%, increasing the offered or actual wage rate of females by 10%, and increasing the respective wage rates of both partners by 10%. For example, increasing male wages may be described as follows

$$C_{w_m+10\%}:(\alpha_m,\alpha_f,\beta_m,\beta_f,w_m,w_f)\mapsto(\alpha_m,\alpha_f,\beta_m,\beta_f,1.1w_m,w_f).$$

We now define the *hours response* to our counterfactual exercise in a given scenario S_k

$$\Delta(\theta,S_k,C)=n(C(S_k(\theta)))-n(S_k(\theta)).$$

Our baseline scenario is given by our estimated parameters θ. We will further consider different aggregation scenarios below. The corresponding *aggregate elasticity* can then be described as

$$\bar{\varepsilon}(S_k,C)=\frac{\int\Delta(\theta,S_k,C)\mathrm{d}F(\theta)}{\int n(S_k(\theta))\mathrm{d}F(\theta)}\approx\frac{\sum\Delta(\theta_i,S_k,C)f_i(\theta)}{\sum n(S_k(\theta_i))f_i(\theta)}, \tag{16}$$

where f_i are normalized sample weights that sum to 1 and i are individual indexes. Since our model is static, all measured elasticities are long-run Marshallian wage-elasticities of market hours. Note that we focus on total hours adjustment which encompasses the induced hours' adjustment by previously employed and by previously non-employed.

It is important to emphasize that for each member in each couple, we get a *posterior sample* of hours responses and elasticities. For example, consider an NE couple where the male is non-employed, while the female is employed. For some combinations of posterior parameters (e.g. male wage close to the reservation wage, which depends on the αs and βs, and the female wage), an 10% increase in male wages can result in employment (EE), or even in the female withdrawing from employment (EN), while for wages further from the reservation wage, the male would remain non-employed regardless of the wage increase (NE). Since we have draws from the posterior distribution, the adjustments in hours are automatically weighted with probabilities of all of these events in hour calculations, and we report expected values that take the nonlinear hours responses and the posterior uncertainty into account.

We estimate an elasticity of 0.056 of male hours to the counterfactual exercise of increasing both male and female wages in a couple. With an elasticity of 0.081, females respond slightly more to the wage increase for both partners. Elasticities are generally small in this counterfactual. Elasticities are substantially larger when the wage of only one partner in the couple is increased. The male own-wage elasticity is estimated to be 0.4 and the corresponding cross-elasticity of females to be -0.955. The female own-wage elasticity is estimated to be 1.034 and the corresponding cross-elasticity of males to be -0.371. Females again react more strongly than men to each type of wage rise.[29]

Our estimation supports that male hours react to female wages at all. In many studies, this possibility is excluded by assumption (e.g. Attanasio et al. (2018)). Figure 6 below plots our estimated

[29] Blau and Kahn (2007) report own-wage elasticities for married women in the US to drop from ca. 0.80 in the 1980s to ca. 0.40 in 2000. Over the same time horizon, their cross-wage elasticities change from -0.40 to -0.20.

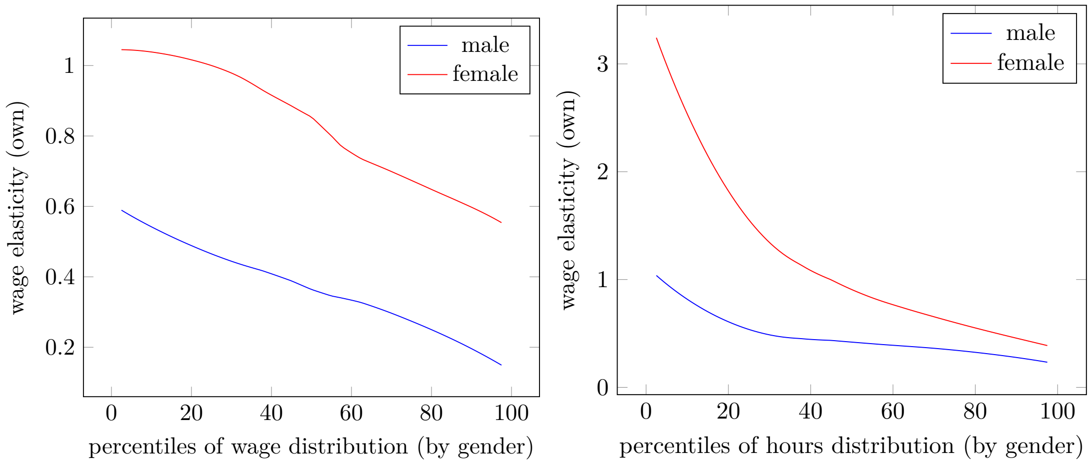

Figure 6: Own-wage elasticities by wage and hours percentile. (Elasticities calculated using 20 bins, with mild LOESS smoothing).

(a) Partition in the data (columns) and after a male wage increase (rows).

	EE			EN			NE			NN		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
NN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00
NE	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
EN	0.00	0.31	-1.63	0.27	0.10	0.00	0.00	0.93	-0.66	0.01	0.49	0.00
EE	0.62	0.59	-1.40	0.00	0.00	0.00	0.02	0.84	-0.46	0.00	0.00	0.00

(b) Partition in the data (columns) and after a female wage increase (rows).

	EE			EN			NE			NN		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
NN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00
NE	0.00	-1.05	0.76	0.00	0.00	0.00	0.06	0.00	0.59	0.01	0.00	0.87
EN	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EE	0.62	-0.60	1.35	0.07	-0.20	1.38	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: Decompositions of elasticities for the estimated model by couple status.

own-wage elasticities for both males and females across percentiles of the underlying wage and hours distribution. Own-wage elasticities decrease in both wages and hours, where the latter effect is much more pronounced, especially for females. While generally higher in level, the overall pattern nicely compares to the long-run Marshallian elasticities for females reported in Figure 3 of Attanasio et al. (2018).

Next, we partition the estimated own-wage and cross-wage elasticities by couple type. Table 3 reports the adjustment of spouses' labor market involvement together with the relative frequency of particular cases. For each type of wage-rise considered, the reaction by dual-career couples (EE) matters most for own- and cross-wage elasticities followed by those of traditional couples (EN). Dual-career couples amount to 62 percent of all partnerships considered. Within these couples, the spouse exposed to the wage hike significantly increases hours while her partner decreases hers.[30]

"Traditional" (EN) couples account for about 27 percent of all partnerships. When male wages rise, men within these couples increase hours, but only weakly. However, when female wages rise, women significantly increase hours while men reduce theirs somewhat, inducing 7 percentage points of all couples moving from being traditional to dual-career. 68 percent of the total change in hours accrues to couples with no partner changing her labor market state. However, the strongest relative change in hours occurs among females in couples which switch from traditional to dual-career.

In sum, males' own-wage elasticity is primarily determined by the 90 percent of dual-career or traditional couples without a change in labor market state of either spouse. However, for females' own-wage elasticity the hours adjustment among the fraction of traditional couples which become dual-career matters in addition to that of dual-career couples. All cross-wage elasticities result from the respective spouse's hours adjustment in reaction to their partners' noticeable rise in hours worked.

6.4 Aggregation bias

We compare four *aggregation scenarios* to our baseline estimation and to each other. An aggregation scenario transforms θ, since we replace some or all parameters with representative values $\bar{\alpha}_m$,$\bar{\alpha}_f$,$\bar{\beta}_m$,$\bar{\beta}_f$,$\bar{w}_m$,$\bar{w}_f$. In our four scenarios we replace estimated preferences (P), wages (W), or both (PW). For example, "representative preferences" is an aggregation scenario that replaces all α,β pairs with $\bar{\alpha}$,$\bar{\beta}$:

$$S_P : (\alpha_m,\alpha_f,\beta_m,\beta_f,w_m,w_f) \mapsto (\bar{\alpha}_m,\bar{\alpha}_f,\bar{\beta}_m,\bar{\beta}_f,w_m,w_f)$$

We calculate these representative values such that they reproduce the average market and leisure hours (weighted by f_i, the representative survey weights for the households) and wages (also weighted by f_i, and hours worked) for males and females. Effectively, this allocation replicates the empirically observed aggregate hours and income resulting from a *representative couple* (RC). We also calculate similar parameters for a *homogeneous couple* (HC). This homogeneous couple is calibrated to have the same α, β, and w for males and females, effectively resulting in three free parameters which are then matched to the average market- and leisure hours and income. This homogenous couple may be compared to alternative models that are based on a representative individual (household). In contrast to a representative individual, whose optimization problem does not feature coordinating with another agent, this homogeneous couple remains directly comparable to the other aggregation exercises. Table 4 shows the calibrated results.[31]

We can now compare measures of males' and females' *own- and cross-wage elasticities* that result from alternative scenarios of aggregation. The main goal of this exercise is (i) to understand the underlying determinants of spouses' own- and cross-wage elasticities in a given scenario, and (ii) to illustrate how these wage-elasticities react upon the outcomes from the various aggregation

[30] This observation indicates that spouses mutually insure each other in the labor market.

[31] Numbers are based on the posterior draws and not directly on the data, for consistency with counterfactuals. They hence differ slightly from weighted sample averages shown in Table 1.

couple type	RC male	RC female	HC (m=f)
market hours	7.10	4.43	5.77
leisure hours	8.54	8.87	8.71
$\bar{w}$	15.64	11.98	14.23
$\bar{\alpha}$	0.47	0.46	0.45
$\bar{\beta}$	0.36	0.51	0.45

Table 4: Calibration of representative couple (RC) and homogenous couple (HC).

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	0.056	0.081		
representative wage	0.048	0.053	−13%	−34%
representative preferences	0.084	0.129	51%	60%
representative wages & preferences	0.052	0.099	−7%	23%
homogeneous couple	0.069	0.069	23%	−15%

Table 5: Responses of hours to a 10% increase in *both* wages (elasticity).

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	0.400	−0.955		
representative wage	0.578	−0.849	45%	−11%
representative preferences	0.452	−1.140	13%	19%
representative wages & preferences	0.633	−1.663	58%	74%

Table 6: Responses of hours to a 10% *male* wage increase (elasticity).

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	−0.371	1.034		
representative wage	−0.583	0.855	57%	−17%
representative preferences	−0.407	1.319	10%	28%
representative wages & preferences	−0.640	1.615	73%	56%

Table 7: Responses of hours to a 10% *female* wage increase (elasticity).

scenarios compared to the implied aggregates of the estimates from the cross-sectional baseline. We refer to the differences in elasticities between the estimated baseline and the representative wage and preference scenario as *aggregation bias.* We use the scenarios in which we aggregate wages or preferences only to understand the intermediate steps, leaving all other parameters unchanged. Tables 5, 6, and 7 show the results.

Table 5 documents the counterfactual exercise of increasing both male and female wages in a couple across aggregation scenarios. Elasticities decrease when aggregating wages only and increase when aggregating preferences only. Comparing the estimated to the representative couple, male elasticities decrease by about 7%, while female elasticities increase by about 23%. This compares to an exercise similar in spirit by Boppart, Krusell, and Olsson (2019) who investigate aggregation bias in Frisch wage elasticities where the unit of investigation is the household. Our model does not imply any substantial aggregation bias when comparing the estimated baseline to the homogenous couple. To summarize, a change in the absolute position of both partners does not affect time allocation much in our model. Similarly, couples interaction does not matter much when partners are equal.

Tables 6 and 7 show male and female own- and cross-wage elasticities across scenarios. For both counterfactuals, we document substantial aggregation bias. For own-wage elasticities, this bias amounts to a 56% and 58% difference in elasticities between the estimated baseline and the representative wage and preference scenario for females and males, respectively. For cross-wage elasticities, aggregation bias is larger, but again very similar across gender. The difference in elasticities equals 74% for females and 73% for males. This exercise shows that aggregation bias is substantial when only one partner in the couple experiences a wage change. When either the male or the female experiences a wage change or when ex-ante wages and preferences are re-assigned, the relative position within the couple changes. It is in these cases that interaction within the couple matters most.

6.5 Decomposing the aggregation bias

We now decompose the difference in own- and cross-wage elasticities of males and females between different aggregation scenarios. We seek to identify the quantitative importance of particular couple types for the overall result. Couple types are defined by each partner's labor market status and the relative position in the distribution of wages and preference parameters. In each aggregation scenario, we capture agents' reactions by the induced sorting of couple types across the various labor market states, and also by each spouse's total adjustment of market hours worked. We first aggregate wages only, then preferences only, and finally we aggregate all parameters. We take stock at each stage.

Our main insights from this exercise are that the reaction of males and females to aggregating wages and preferences is not different *per se*. What matters most for explaining the size and direction of the aggregation bias in the various wage-elasticities we consider is the distribution of couples across the wage and preference parameter space. The size and direction of a change in market hours is most decisive for a change in the respective wage-elasticities (see also Attanasio et al. (2018)).

There are two mechanisms at work that generate the change in elasticities between aggregation scenarios. First, wage aggregation can be thought of as re-assigning different wages to both partners in a couple. A person's hours react positively to a rise in one's own-wage, since the substitution effect exceeds the income effect in our model, and her market hours react negatively to a rise in her partner's wage because of mutual insurance. Second, preference aggregation can be thought of as re-assigning different preferences to both partners in a couple. The own-wage elasticity declines in the rise of one's own α and rises in the partner's α. That is because a rise in one's own α lets own market hours rise, too, and the own-wage elasticity drop. As the partner's α rises, the partner increases hours while the spouse considered decreases hers which lets her own-wage elasticity rise.

6.5.1 Decomposition method

Let us index different aggregation scenarios by 1 and 2. We define the *midpoint* of baseline hours as $\bar{n}_m = \frac{\bar{n}_1+\bar{n}_2}{2}$. We then separate the effect from the change in *baseline hours* from the change in the *response in hours* when comparing scenarios. For example, the female hours for a specific couple might respond more *proportionally* because the absolute value of the response changed, which we call the "response" effect, *or* because under some counterfactual scenario, these hours were lower to start with, which we attribute to the "baseline". Specifically,

$$\bar{\varepsilon}_2 - \bar{\varepsilon}_1 = \frac{\bar{\Delta}_2}{\bar{n}_2} - \frac{\bar{\Delta}_1}{\bar{n}_1} = \underbrace{\overbrace{\frac{1}{\bar{n}_m}}^{a_\Delta}\left(\bar{\Delta}_2 - \bar{\Delta}_1\right)}_{\text{change in responses}} - \underbrace{\overbrace{\frac{\bar{\varepsilon}_1+\bar{\varepsilon}_2}{2\bar{n}_m}}^{a_n}(\bar{n}_2-\bar{n}_1)}_{\text{change in baselines}} = a_\Delta\left(\bar{\Delta}_2-\bar{\Delta}_1\right) - a_n(\bar{n}_2-\bar{n}_1)$$

The intuition behind the signs of coefficients a_Δ and a_n is simple: a larger response will increase, while a larger baseline will decrease elasticities. It is important to note that this decomposition is *symmetric*: we can exchange the two scenarios and the signs will just flip. This is our main reason for decomposing around the midpoint.

We then decompose this difference $\bar{\varepsilon}_2 - \bar{\varepsilon}_1$ along various cross-sectional dimensions. We introduce a *partition* with *cells* $P_1 \sqcup P_2 \sqcup \ldots$ of $i=1,\ldots$ which we index by l. Our decomposition is then given by

$$\bar{\varepsilon}_2 - \bar{\varepsilon}_1 = \sum_l (\underbrace{\hat{\Delta}_l + \hat{n}_l}_{\hat{\varepsilon}_l})\hat{f}_l, \tag{17}$$

where $\hat{f}_l = \sum_{i\in P_l} f_i$, $\hat{\Delta}_l = a_\Delta \frac{\sum_{i\in P_l}(\Delta_2(\theta_i)-\Delta_1(\theta_i))f_i}{\hat{f}_l}$ and $\hat{n}_l = -a_n \frac{\sum_{i\in P_l}(n_2(\theta_i)-n_1(\theta_i))f_i}{\hat{f}_l}$. Intuitively, $\hat{\Delta}_l$ and $\hat{n}_l$ are (weighted) means of the contributions of various cells to the overall elasticity difference. Since weights sum to 1, it is important to note that $\hat{\Delta}_l$ and $\hat{n}_l$ are in the same "units" as differences between elasticities — this helps to interpret the decomposition as a weighted average.

We show the results of these decomposition exercises with multiples of small bar plots, illustrated as Figure 7. The total frequency f_l is proportional to the *width* of the bars, while the *height* of the bars is proportional to the total $\hat{\varepsilon}_l$, the contribution of the changes in elasticity $\hat{\Delta}_l$ plus the effect of the baseline $\hat{n}_l$. The solid horizontal line corresponds to 0, while the dashed line shows the total difference $\bar{\varepsilon}_2 - \bar{\varepsilon}_1$ in elasticities. Vertical and horizontal scales are fixed throughout the paper, making visual comparison of magnitudes easier.

In the following, we show these decompositions for different aggregation scenarios and own and cross-wage elasticities partitioned by couple types. In Figures 8 and 9 (and also Figures 18 and 17 in the appendix), the plots in the panels of the top and the middle row of any column show the decomposition by couples' labor market status before and after the aggregation, respectively, as well as by quartile of the estimated parameter considered, that is, before the counterfactual experiment. Hence, the groups within the parameter quartiles in corresponding plots are the same. When comparing the mass of couples (width of the bars) within wage quartile between the estimated cross-section (top row) and the representative-parameter scenario (middle row), one identifies the ones that change employment status.

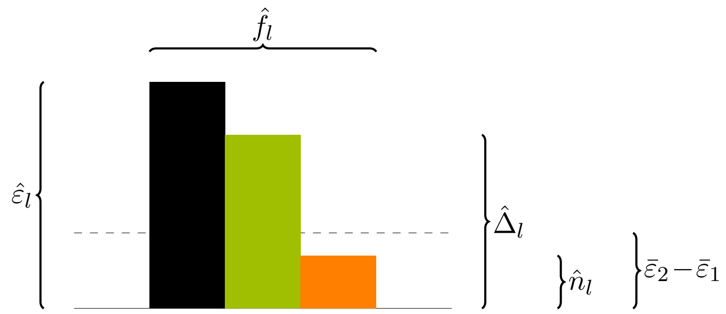

Figure 7: Graphical decomposition of partitioned elasticity differences — see (17).

6.5.2 Wage aggregation

In this section we will focus on the part of the total aggregation bias that arises from wage aggregation only. Across all wage-elasticities considered, we observe two types of reactions upon wage-aggregation. First, high-wage individuals tend to receive a lower wage and therefore reduce their market hours, whereas low-wage individuals enjoy a wage rise and work more. Second, there is an interaction effect at work which captures the fact that spouses tend to adjust their market hours in opposite directions and may move between employment and non-employment. These reactions are consistent with our model's predictions discussed in Section 4.4. Whether the resulting changes in market hours lead to a rise or a decline in the net aggregate wage-elasticity ultimately depends on the distribution of couples across their joint wage distribution.

Figure 8 depicts the aggregation-induced adjustment underlying males own-wage elasticity (left column) and females cross-wage elasticity (right column). We focus the discussion below on these elasticities. [32]

Let us first look at men's own-wage elasticity which rises compared to our benchmark (indicated by the dashed line above the solid line representing the benchmark). Notably, the impact of aggregating wages differs by the level of the initial wage-rate. Wage aggregation causes some low-wage males to move into employment and increase their market hours. These men belong to couples which move from NN to EN, or from NE to EE. On the other hand, high-wage males reduce their hours while remaining employed ($\hat{n}_l < 0$), thereby inducing their female partners to enter employment and to switch the couple's status from EN to EE. These males' own-wage elasticity rises ($\hat{\Delta}_l > 0$). The plots in the panels of the middle and the bottom row indicate that it is mostly high-wage males in dual-earner couples with female partners whose wage lies below the top quartile whose reactions drive the increase in mens own-wage elasticity. Their dominant reaction is slightly counteracted by low-wage males whose female partners earn a high wage. Upon wage aggregation these men tend to increase their market hours relatively strongly ($\hat{n}_l > 0$), thereby reducing their own-wage elasticities. Hence, the contribution to the rise in men's own-wage elasticity is larger when couples are unequal with respect to their wages.

When wages are aggregated, females reduce their market hours less strongly in reaction to a rise in male wages compared to our benchmark which amounts to a slight rise in their cross-wage

[32] We relegate the illustration of the adjustment underlying females own-wage and males cross-wage elasticity in Figure 17 and the accompanying discussion to Appendix F.

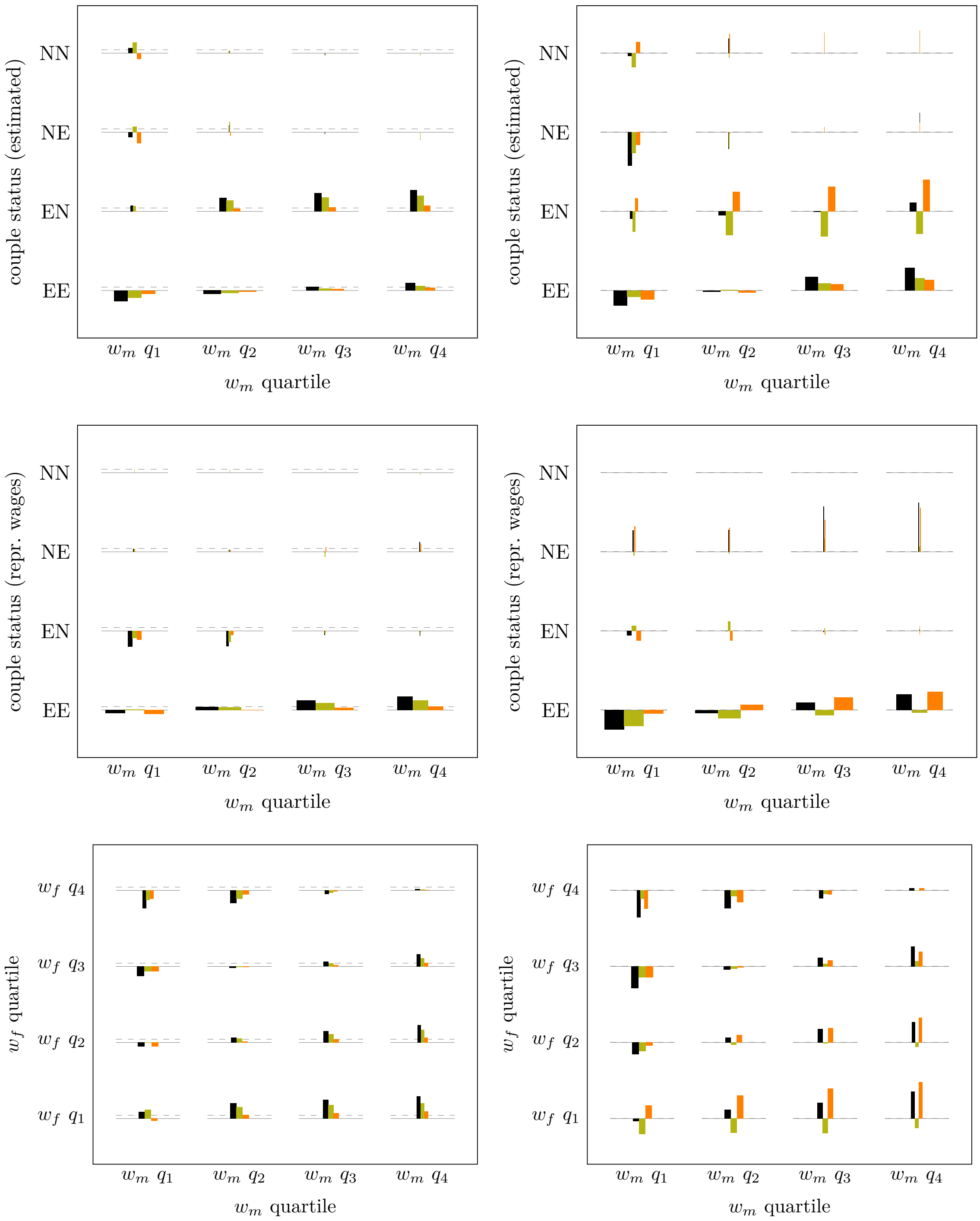

Figure 8: Decomposition of aggregation bias between estimated model and wage aggregation for male own-wage elasticities (left) and female cross-wage elasticities (right). Color legend: total, $\hat{\Delta}$, $\hat{n}$, - - - difference in aggregate elasticity, —— 0; decomposition figure scales are consistent, and thus comparable throughout the paper.

elasticity (indicated by the dashed line above the solid line). This change is concentrated among females whose partner's wage lies above the mean and who either belong to dual-earner couples or who become the sole earner. Females in this group have wages below the top quartile. They tend to reduce market hours less strongly when wages are aggregated, and this adjustment rises in their partner's wage. They do so mainly to partly compensate for their partner's reduced work hours in reaction to wage aggregation. There are opposite reactions among high-wage females with a low-wage partner, but they are too weak to overturn the impact that females with high-wage partners have on the outcome.

6.5.3 Preference aggregation

In this section we will focus on the part of the total aggregation bias that arises from aggregating preferences only. Like before, we study the implied change in couples' employment status or their adjustment of market hours in order to identify the couple types that matter most. We center our discussion around spouses market hours reacting to aggregating the preference parameter α in particular, since β does not stratify our results. Therefore, aggregating by β provides no information on the sub-groups in our sample that matter most for the total bias.

Figure 9 depicts the aggregation-induced adjustment underlying males own-wage elasticity (left column) and females cross-wage elasticity (right column). To maintain the string of arguments we developed in the previous section, we continue to focus our discussion on these elasticities. We relegate illustrating the adjustment underlying females own-wage and males cross-wage elasticity to the appendix.[33]

Across all wage-elasticities considered, we observe that when preferences are aggregated, all but those individuals whose α lies in the bottom quartile receive a lower α and therefore reduce their market hours which *ceteris paribus* leads to a rise in the own-wage elasticity and a drop in the cross-wage elasticity. This finding is consistent with the evidence depicted in the plots in the middle row of Figure 3. Preference aggregation amounts to a drop in the α for the bulk of males and females in dual-career couples. This finding is also consistent with our model's predictions from Section 4.4.

We first look at men's own-wage elasticity which slightly rises compared to our benchmark (indicated by the dashed line above the solid line). Almost all of this rise is concentrated among men in dual-career couples with an α in the top quartile. When preferences are aggregated, men in dual-career couples are assigned a smaller α which leads to a reduction in their market hours and a rise in their own-wage elasticity. The size of the reaction of men's market hours declines and that of their own-wage elasticity rises in their female partner's α, because men's hours partially offset the females' hours reduction when preferences are aggregated. These reactions are partly offset by men in traditional couples whose α lies below the mean and whose female partners have an above average α.

Compared to our benchmark females reduce their market hours more strongly when male wages rise under preference aggregation (indicated by the dashed line below the solid line). This amounts to a decline in females cross-wage elasticity. Preference aggregation causes relatively many females to increase their market hours. The bulk of this adjustment once more occurs among women in

[33]See Figure 18 and the accompanying explanation in Appendix F.

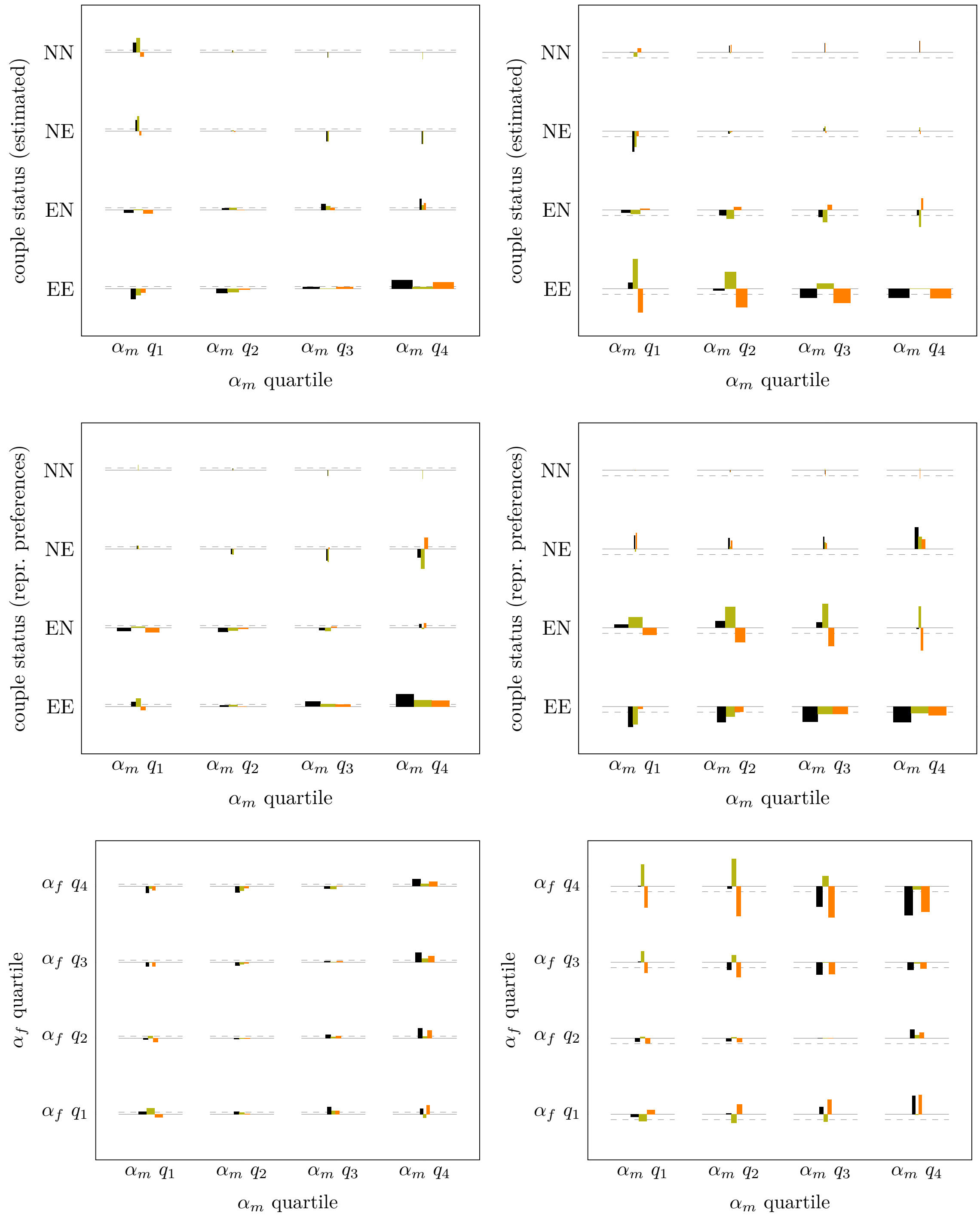

Figure 9: Decomposition of aggregation bias between estimated model and preference aggregation for male own-wage elasticities (left) and female cross-wage elasticities (right). Color legend: ▬ total, ▬ $\hat{\Delta}$, ▬ $\hat{n}$, - - - difference in aggregate elasticity, —— 0; decomposition figure scales are consistent, and thus comparable throughout the paper.

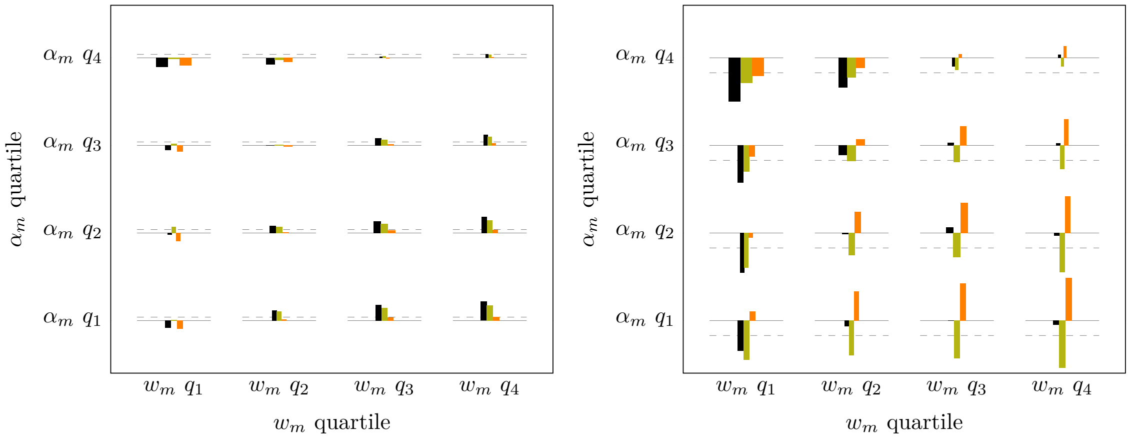

Figure 10: Decomposition of aggregation bias between preference aggregation and preference and wage aggregation for males' own-wage elasticities (left) and females' cross-wage elasticities (right). Color legend: ▬ total, ▬ $\hat{\Delta}$, ▬ $\hat{n}$, - - - difference in aggregate elasticity, —— 0; decomposition figure scales are consistent, and thus comparable throughout the paper.

dual-earner couples. Within this group, the stronger increase in market hours is concentrated among females with a high α particularly when they are partnered with high α males. Why is this so? Preference aggregation assigns both spouses a smaller α inducing females to reduce market hours, but they also compensate for the loss in earnings due to their partner reducing his hours which is larger for larger α_m. The compensation effect dominates.

6.5.4 Wage and preference aggregation

We are now in a position to discuss the adjustments that occur when we simultaneously aggregate wages and preferences. We continue to focus our discussion on the adjustments underlying the bias in men's own-wage elasticity and in females' cross-wage elasticity, relegating the remaining discussion to the appendix.

In order to understand the underlying forces at work, it is instructive to show the decomposition moving from aggregating preferences only to simultaneously aggregating wages and preferences. That way we can identify reactions that enhance each other and those that offset each other in terms of their impact on the various wage-elasticities considered. Figure 10 depicts the adjustments underlying males' own-wage elasticity (left panel) and those underlying females' cross-wage elasticity (right panel).

Compared to the cross-sectional baseline, aggregating wages and preference parameters leads to a rise in males own-wage elasticity by 58 percent (indicated by the dashed line above the solid line in the left panel of Figure 10). The middle and bottom left panels in Figure 9 show that the part of this rise that is due to preference aggregation is concentrated among dual earner couples where males have a rather high α. Preference aggregation leads to a reduction of their work hours and a rise in their net own-wage elasticity. The left panel of Figure 10 depicts the additional adjustment that is due to subsequently also aggregating wages. We observe that the rise in males own-wage elasticity is concentrated among men with an above average wage rate and an α that lies below the top quartile. Wage aggregation lets them reduce market hours which raises their own-wage elasticity. The group of high α men who reduced their hours worked upon preference aggregation *raise* their hours upon wage aggregation, thereby slightly counteracting the overall increase in men's own-wage elasticity without overturning it.

Full parameter aggregation lets females' reduce their market hours much more strongly when male wage rates rise than in the baseline scenario. (The reduction in the aggregate females' cross-wage elasticity is depicted in the right panel to Figure 10 by the dashed line lying below the solid line.) This change amounts to a rise by 74 percent in absolute terms. To understand the underyling forces recall that preference aggregation only leads to a relatively small decline in this elasticity and that this decline is concentrated among women in dual-earner couples who have a high α and whose partner also has a high α. Adding wage aggregation significantly strengthens this decline. This is because of females whose male partners have a very low wage rate. Table 18 in the appendix suggests that these females tend to have low wage rates themselves, so that wage aggregation lets their wage rate and their market hours rise. As a result, their cross-wage elasticity is strongly reduced.

6.6 Robustness with respect to the share in home production

In our baseline analysis, we have fixed γ at the value of 0.5. As we explain in Section 5.1, γ cannot be identified in our setup from allocation information alone. We do not pursue identification of γ in the context of this model, since we suspect an estimated value would be driven by incidental assumptions such as the tail shape of distributions in (15) which we parametrized with a multivariate normal for convenience. Instead, we consider the results to two alternative cases in which we decrease the male share in home production, γ, to 0.3 and increase it to 0.7, respectively. Figure 11 shows the estimated cross-sectional marginal posterior densities when $\gamma = 0.3$ (in a comparable format to Figure 3). The respective plot for $\gamma = 0.7$ is exhibited in the appendix (Figure 20). A lower γ leads to a lower α_m and β_f and a higher α_f and β_m on average as depicted in the shift of the respective marginal posterior distributions. When men are not as productive at home, men need to value market consumption less and the consumption of home goods more in order to rationalize the same observed hours allocation as men that are more productive. The opposite happens for women which are more productive at home when γ is lower. Following the same argument, the estimated market wage w_m is lower and w_f is higher when γ is lower.

Tables 8 to 10 show the estimated elasticities together with the various aggregation exercises when $\gamma = 0.3$. The respective tables for $\gamma = 0.7$ can be found in the appendix (Tables 24 to 26). Most importantly, the estimated elasticities are hardly affected by changing γ. The reason is that γ and the preference parameters jointly determine the labor supply elasticities and change such that their respective effects offset each other. Consider for example the labor supply elasticity of EE couples as described in section 4.4. This elasticity falls in own α and market wage, but increases in the partners parameters. Table 16 in the appendix compares root mean squared deviations across different values of γ. The model fit is very good and comparable across cases, our baseline parametrization is not dominated when varying γ.

When aggregating parameters, the direction of the aggregation bias is generally similar across

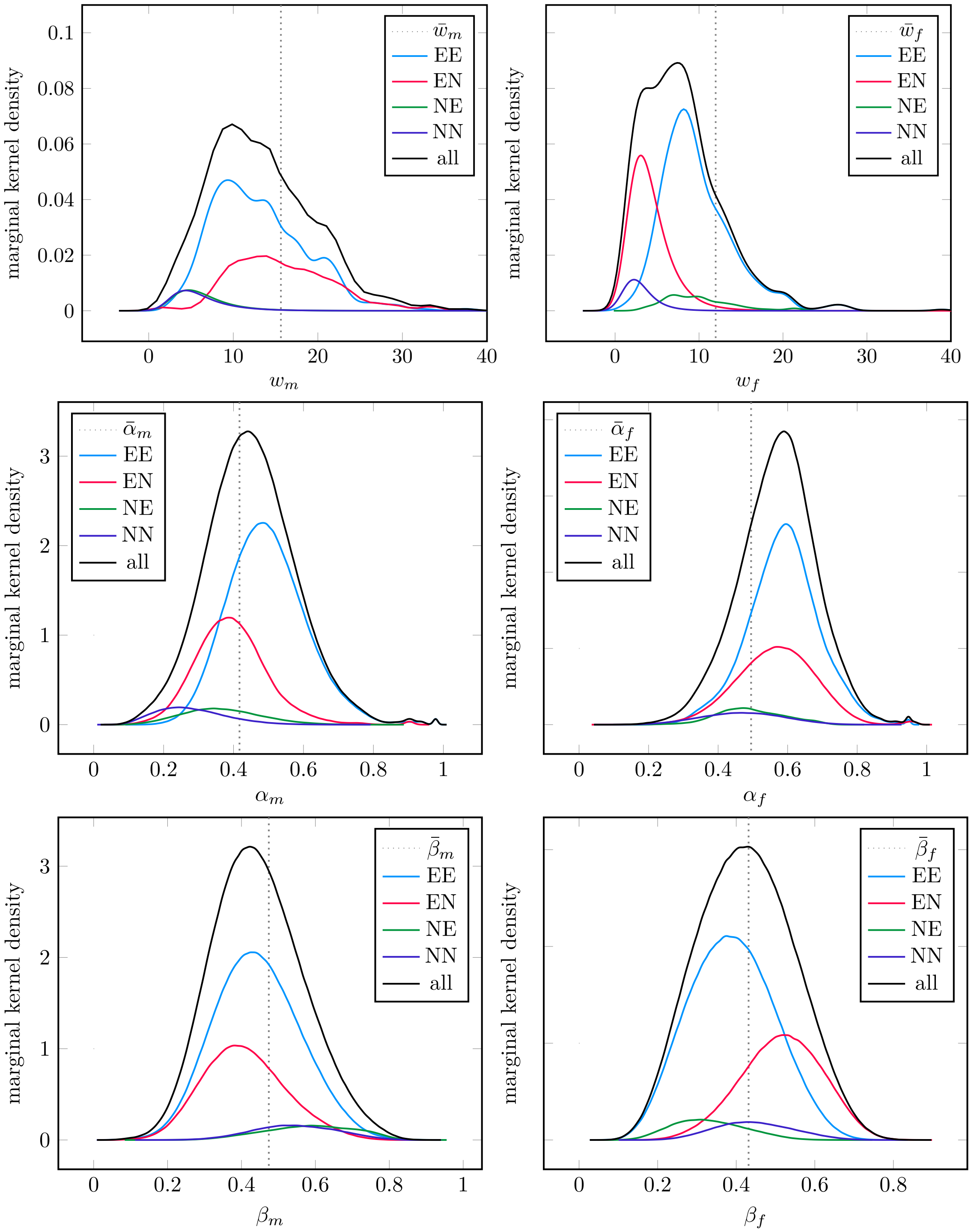

Figure 11: Cross-sectional marginal posterior densities with $\gamma = 0.3$.

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	0.056	0.080		
representative wage	0.048	0.052	−14%	−36%
representative preferences	0.089	0.117	59%	46%
representative wages & preferences	0.052	0.099	−7%	23%
homogeneous couple	0.093	0.093	65%	15%

Table 8: Responses of hours to a 10% increase in *both* wages (elasticity) with $\gamma = 0.3$.

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	0.402	−0.951		
representative wage	0.614	−0.774	53%	−19%
representative preferences	0.446	−1.127	11%	18%
representative wages & preferences	0.637	−1.656	59%	74%

Table 9: Responses of hours to a 10% *male* wage increase (elasticity) with $\gamma = 0.3$.

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	−0.372	1.033		
representative wage	−0.617	0.775	66%	−25%
representative preferences	−0.394	1.284	6%	24%
representative wages & preferences	−0.644	1.608	73%	56%

Table 10: Responses of hours to a 10% *female* wage increase (elasticity) with $\gamma = 0.3$.

different aggregation scenarios and values of γ. The aggregation bias when aggregating wages or preferences only can be larger in size in some cases when γ is low or high. That's because if γ is more extreme, some values of preferences and estimated wages need to be extreme, too, in order to explain the observed time allocation for some groups. Then, re-assigning preferences and wages in the aggregation exercises has large effects for these groups. However, as explained above, changing γ affects both preferences and wages such that their respective effects cancel with respect to labor supply elasticities. Hence, when both wages and preferences are aggregated, extreme effects cancel each other and, as a consequence, the choice of γ does not substantially affect the aggregation bias when aggregating both wages and preferences.

7 Conclusion

We study the role of heterogeneous preferences and wages of spouses who interact in their time-allocation decisions for the labor supply of couples. We allow for heterogeneity within and across couples in preferences for market consumption goods and non-market goods and activities, and also in actual or offered wage-rates. In this setting, all agents endogenously sort into market work, or homework and leisure, yielding as equilibrium outcome dual-career couples, those with only one spouse employed, and couples where neither partner works in the market. The model is consistent with the empirical evidence that even in couples where at least one member is employed, spouses' choices of hours worked in the market and at home are heterogeneous.

We estimate our model using Bayesian techniques and micro data from the 2001/02 wave of the German Time-Use Survey. Our sample contains married or cohabiting couples without young children where each spouse is of prime working-age. We take the estimated model as our benchmark and use it as a lab for two types of counterfactual exercises. First, we generate the full spectrum of males' and females' own-wage and cross-wage elasticities in the cross section. Because we are using a static model, all elasticities are of Marshallian type. They measure the induced change in market hours by individuals who were previously employed or non-employed. For each type of elasticity we can disentangle the quantitative contribution of spouses living in single- or dual-earner couples and the direction and size of each spouse's hours adjustment in reaction to wage shocks.

Our estimates are of plausible size and show a familiar pattern: females' wage-elasticities always exceed in absolute terms the male counterpart, and own-wage elasticities decline in the wage rate. All elasticities are an order of magnitude larger when generated from an asymmetric rise in either the male or the female wage-rate than when both wages rise symmetrically. This result is due to spouses mutually insuring variations in income which matters most when wage-shocks are asymmetric. Second, we aggregate preference parameters and wage rates by gender and compare wage-elasticities for a *representative couple* with their counterparts derived from our benchmark featuring heterogeneous couples. We find that the bias in aggregate wage-elasticities between these two scenarios is larger under asymmetric wage shocks across spouses than under symmetric ones, and that the size of the bias depends on the distribution of spouses across the space of preference parameters and wage rates. In fact, we find that an identical bias in a given wage-elasticity across sexes can reflect very different underlying patterns of adjusting hours worked for men and women.

Our results show why modelling heterogeneity at the spousal level matters for macroeconomics and also for macroeconomic policy analysis that involves the labor market. Aggregate wage-elasticities of market hours not only depend on the type of aggregation implemented, and on the distribution of couples across the space of preference parameters and wage rates. Their size also depends on whether wage shocks are asymmetric or symmetric across spouses. Our framework contains crucial ingredients for studying the implications of particular non-linear policies at the spousal level and their impact on labor supply. For example, by introducing labor income taxes or transfers, we could not only assess their incidence on different types of couples, but also study their implications for aggregate labor supply by wives and husbands.

We believe that our rich analytical setting lends itself to studying important issues related to couples' time-allocation. For example, empirical evidence suggests that women in industrialized countries have steadily increased their educational achievements which has contributed to an improved assortative mating of partners by wages. This change most likely impacts spousal time-allocation, and also wage-elasticities in the cross-section and in the aggregate.

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A Additional graphs and tables for data

household type	German TUS	Microcensus
couples		
without kids	17.9	20.8
with kids above 6 years	35.2	38.1
with kids below 6 years	21.3	3.1
singles		
without kids	16.0	17.2
with kids	7.0	6.6
other	2.6	14.2

Table 11: Population shares by marital status. Numbers show percentages in population between 25 and 54 years old. Microcensus refers to year 2000.

	Mean	Std. Dev.	25%	50%	75%	Min.	Max.
			Full sample				
market work, female	4.22	3.41	0	4.67	7.17	0	12.3
market work, male	7.13	2.81	6.67	7.83	8.67	0	14
home prod., female	4.94	2.75	2.83	4.50	6.83	0.17	13.8
home prod., male	2.23	1.74	1	1.83	3	0.17	11
leisure, female	8.84	2.26	7.25	8.58	10.1	3.17	17.5
leisure, male	8.64	2.19	7.33	8.33	9.50	2.83	17.7
			EE				
market work, female	6.34	1.99	4.67	6.25	7.83	2.17	12.3
market work, male	7.92	1.63	7.08	8	8.83	2.67	14
home prod., female	3.70	1.89	2.25	3.50	5	0.17	8.83
home prod., male	1.98	1.30	0.92	1.83	2.83	0.17	8.83
leisure, female	7.96	1.67	6.83	7.92	8.92	3.17	15
leisure, male	8.09	1.61	7.08	8.17	9	2.83	13.5
			EN				
market work, female	0	0	0	0	0	0	0
market work, male	7.86	1.61	7	7.83	8.67	2.17	13.2
home prod., female	7.67	2.37	6.25	7.83	9.33	0.50	13.8
home prod., male	1.73	1.22	0.83	1.50	2.25	0.17	8.50
leisure, female	10.3	2.37	8.67	10.2	11.8	4.17	17.5
leisure, male	8.41	1.64	7.42	8.42	9.33	4.17	14.7
			NE				
market work, female	6.59	1.73	5.17	6.67	7.92	3.67	10.5
market work, male	0	0	0	0	0	0	0
home prod., female	2.94	1.67	1.75	2.92	4.17	0.17	7.50
home prod., male	5.47	2.75	3.58	5.42	7.50	0.33	11
leisure, female	8.47	1.48	7.50	8.42	9.08	5.17	13.3
leisure, male	12.5	2.75	10.5	12.6	14.4	7	17.7
			NN				
market work, female	0	0	0	0	0	0	0
market work, male	0	0	0	0	0	0	0
home prod., female	6.40	1.93	4.96	6.25	7.75	1.58	10.4
home prod., male	4.99	2.05	3.63	4.50	6.54	0.50	10.3
leisure, female	11.6	1.93	10.3	11.8	13.0	7.58	16.4
leisure, male	13.0	2.05	11.5	13.5	14.4	7.75	17.5

Table 12: Detailed descriptive statistics: daily total market work, total home production and leisure, in hours. Entire sample and by couple type. Not weighted with population weights.

Variables	CMW, f	CMW, m	THP, f	THP, m	Leisure, f	Leisure, m
CMW, f	1.000					
CMW, m	0.098	1.000				
THP, f	-0.751	0.033	1.000			
THP, m	0.032	-0.626	-0.007	1.000		
Leisure, f	-0.597	-0.189	-0.081	-0.041	1.000	
Leisure, m	-0.152	-0.785	-0.036	0.008	0.274	1.000

Table 13: Correlation of time use variables. CMW denotes core market work, THP total home production, f denotes female and m male.

	EE	EN	NE	NN
hourly wage male	13.21	27.90		
	(5.835)	(148.5)		
hourly wage female	11.51		10.00	
	(28.64)		(4.137)	
non-labor income	227.5	371.8	1092.6	1654.0
	(429.9)	(514.8)	(881.2)	(733.7)
age male	44.28	45.18	45.62	46.45
	(5.908)	(5.111)	(5.881)	(6.121)
age female	41.82	42.61	42.55	43.45
	(5.942)	(5.067)	(5.319)	(6.170)
frac. univ. degree male	0.199	0.258	0.128	0.0909
	(0.400)	(0.439)	(0.337)	(0.291)
frac. univ. degree female	0.152	0.107	0.0426	0.0455
	(0.359)	(0.310)	(0.204)	(0.211)
frac. fh degree male	0.155	0.148	0.149	0.0909
	(0.363)	(0.355)	(0.360)	(0.291)
frac. fh degree female	0.143	0.0738	0.128	0.0682
	(0.350)	(0.262)	(0.337)	(0.255)
frac. meister male	0.126	0.133	0.0851	0.114
	(0.332)	(0.340)	(0.282)	(0.321)
frac. meister female	0.0314	0.00738	0.0638	0.0227
	(0.175)	(0.0857)	(0.247)	(0.151)
frac. high school male	0.279	0.310	0.213	0.205
	(0.449)	(0.463)	(0.414)	(0.408)
frac. high school female	0.290	0.207	0.106	0.0682
	(0.454)	(0.406)	(0.312)	(0.255)
Observations	1,146	542	94	88

Table 14: Couples by spouses' labor market status in the 2001/2002 wave. Table shows means of variables with standard deviations in percentages, not weighted with population weights. Hourly wages are denoted in Euro. Education refers to fractions of persons in each education group, remaining persons belong to other groups. *fh* refers to university of applied sciences and *meister* refers to the master craftsman certificate.

income source	household type				total
	EE	EN	NE	NN	
capital income/property	0.2	0.7	2.1	4.5	0.6
employment	86.7	88.6	53.2	2.3	81.6
other public support	0.0	0.0	4.3	0.0	0.2
pension	0.2	0.0	19.1	22.7	2.1
self-employed/agriculture	12.4	10.7	6.4	2.3	11.1
social security	0.0	0.0	0.0	2.3	0.1
unemployment benefits	0.0	0.0	14.9	63.6	3.7

Table 15: Main source of income by household labor market status. Notes: 2001/2002 sample. Together with missing values the columns add to 100%.

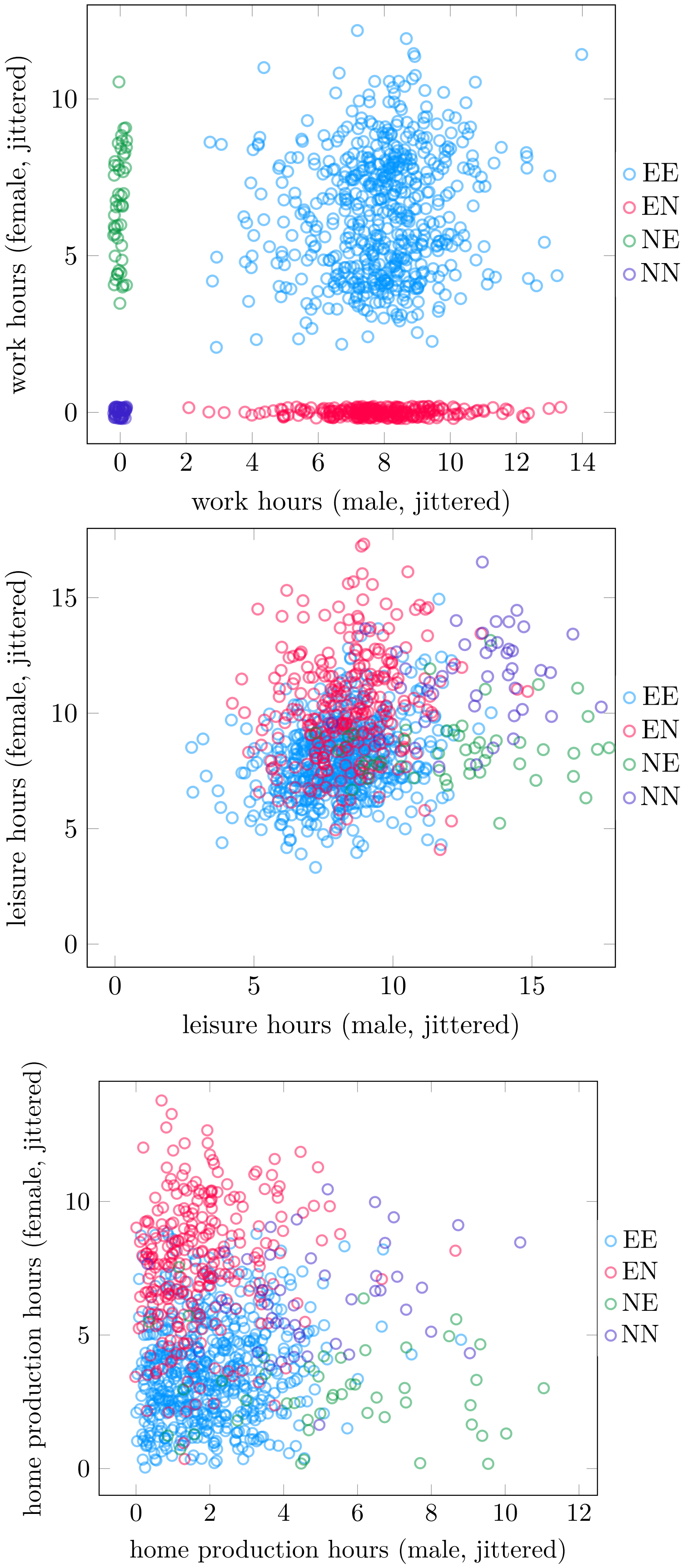

Figure 12: Scatterplots of average daily work, leisure, and home production hours by each partner's labor market status.

B Summary of notation

	indexing data
$j \in \mathcal{C}$, $i \in \mathcal{I}$	indexes for couples and individuals
	model setup
$i = m, f$	individual's index (male, female)
k	the "other" individual in a couple
α_i	preference parameter (consumption vs home and leisure), see (4)
β_i	preference parameter (home prod vs leisure, see (4))
γ_i	exponent in home production function, see (3)
M	total non-wage income for couple
T_i	time endowment for each individual
n_i	market (work) hours
h_i	home production hours
ℓ_i	leisure hours
z	home production
c	joint consumption
w_i	wages for individual
	model characterization
η_i	share of market hours n_i out of T_i
ν_i	share of leisure out of $T_i - n_i$ (5)
ϕ_i	key parameter that governs market time choice, (8)
	Bayesian model
X_i	individual covariates (sex, age)
B	regression coefficient on individual covariates, (15)
Σ	covariance matrix for cross-sectional parametric distribution, (15)
$\sigma_\Sigma, \Omega, \sigma_\nu, \sigma_\eta$	noise parameters, see Section 5.2
	Results
$\bar{\varepsilon}$	aggregate elasticity, see (16)
$\bar{\alpha}_i, \bar{\beta}_i, \bar{w}_i$	representative parameters, see Table 4
$\hat{\Delta}_l, \hat{n}_l, \hat{\varepsilon}_l, \hat{f}_l$	partitioning of elasticity differences, see (17)

C Common algebraic form for market hours

In order to unify the algebra, we transform the optimization problems for market hours n to the form

$$\max_{0 \le n \le T} (\tilde{M} + nw)(T - n)^\phi \tag{18}$$

where $w = w_i$ and $n = n_i$ for members of a couple, and $\tilde{M} = M + n_k w_k$ would include the earnings for the partner.

For an interior solution, this has the FOC

$$w(T-n)^\phi = \phi(\tilde{M} + nw)(T-n)^{\phi-1} \qquad \Leftrightarrow \qquad n = \frac{T - \phi\frac{\tilde{M}}{w}}{1+\phi}$$

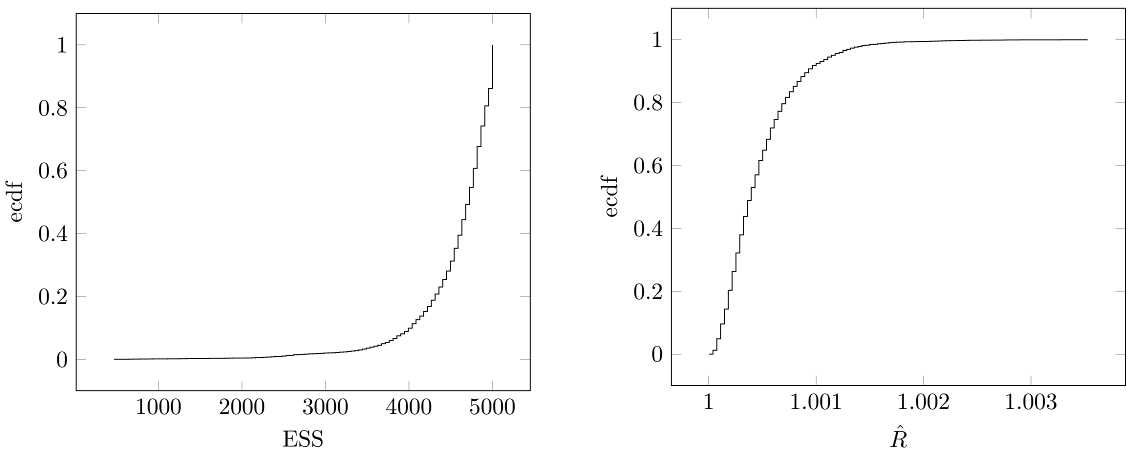

Figure 13: MCMC diagnostics. Left: effective sample size (ESS), right: and potential scale reduction ($\hat{R}$), as empirical cumulative distributions. 5×1000 samples after warmup.

Consequently, considering the constraint, the solution to (18) is

$$n = \begin{cases} 0 & \text{if } Tw \leq \phi \tilde{M} \\ \frac{T - \phi \tilde{M}/w}{1+\phi} & \text{otherwise.} \end{cases}$$

Intuitively, one can think of $\tilde{M}/T$ as a wage-like quantity for the endowment of the individual, which determines the marginal value of leisure. This is compared to the market wage, using the preference parameter ϕ.

D MCMC diagnostics and prior-posterior comparisons

Figure 13 shows the effective sample size and the potential scale reduction for the MCMC run (5 chains, default NUTS warmup, 1000 in each chain samples after warmup). Both statistics indicate good mixing and convergence. We also checked NUTS-specific statistic (eg divergence, reaching maximum tree depth) and they are do not suggest any problems with convergence either.

E Posterior checks

Figure 15 compares the fraction of time spent on market work (η) and leisure out of the rest (ν) in the data (horizontal axes) with the predicted posterior average (vertical axes) for men and women. Table 16 shows the root mean squared deviation of the fraction of time spent of market work for males and females. In the baseline, this measure is 2.6% for males and 1.8% for females. Confirming the visual inspection from Figure 15, the model therefore fits the variation in market hours fairly well. While the model fits market hours rather well, and predicts employment status by construction, the share of leisure-home production hours is not replicated perfectly away from their means, especially for workers who have a leisure fraction ν near 1. Since we focus on analyzing market hours, we leave improving the model along this dimension for future research.

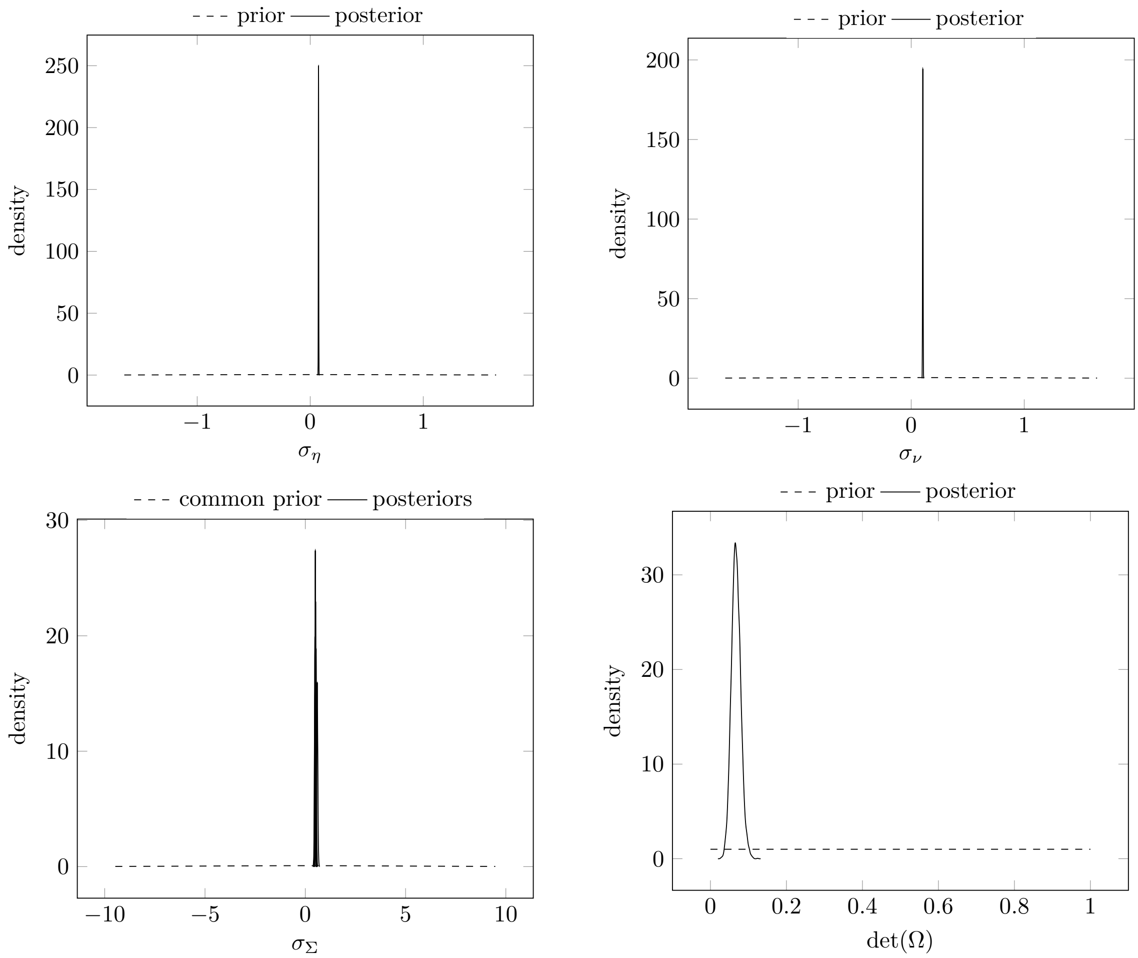

Figure 14: Comparison of priors (dashed) and posteriors (solid). The range is always 5%–95% quantiles of the prior.

	η_m	η_f
baseline	0.026	0.018
$\gamma = 0.3$	0.024	0.020
$\gamma = 0.7$	0.026	0.015

Table 16: Root mean squared deviation of η for different γ

Table 16 also compares the root mean squared deviation of the fraction of time spent of market work for different values of γ. The model performs similarly well for different values of this parameter. In case of low γ, the fit slightly improves for males and worsens for females, $\gamma = 0.7$ worsens the fit for females. Hence, our baseline value of $\gamma = 0.5$ performs reasonably well.

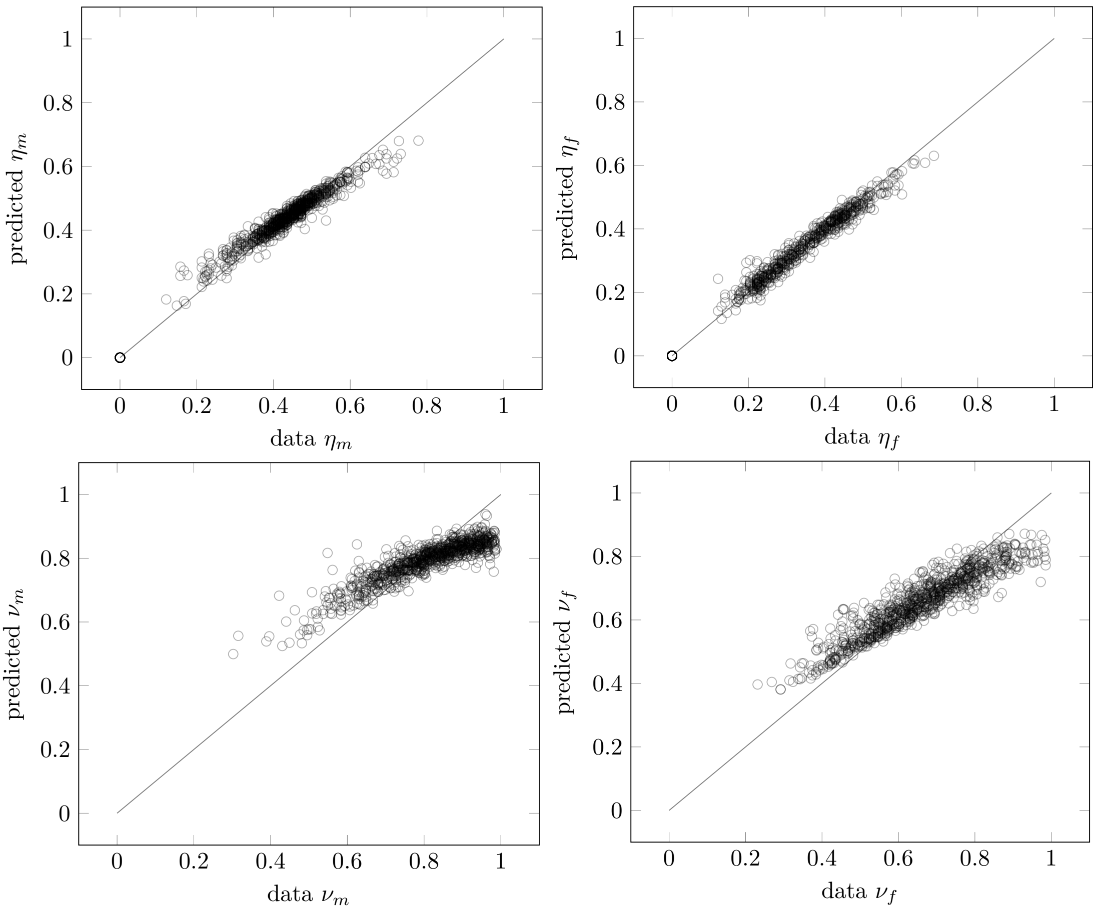

Figure 15: Predicted vs data time use (market η fraction, leisure fraction ν).

	5%	25%	50%	75%	95%
σ_η	0.07	0.07	0.07	0.07	0.08
σ_ν	0.10	0.10	0.10	0.10	0.11
$\sigma_\Sigma[1]$	0.49	0.51	0.52	0.53	0.54
$\sigma_\Sigma[2]$	0.44	0.46	0.48	0.50	0.52
$\sigma_\Sigma[3]$	0.48	0.49	0.50	0.51	0.52
$\sigma_\Sigma[4]$	0.50	0.52	0.54	0.55	0.57
$\sigma_\Sigma[5]$	0.45	0.47	0.48	0.49	0.51
$\sigma_\Sigma[6]$	0.56	0.58	0.60	0.62	0.65
$\Omega[1,2]$	-0.50	-0.45	-0.42	-0.38	-0.34
$\Omega[1,3]$	-0.25	-0.22	-0.19	-0.17	-0.13
$\Omega[1,4]$	0.08	0.13	0.16	0.19	0.23
$\Omega[1,5]$	-0.28	-0.24	-0.21	-0.18	-0.13
$\Omega[1,6]$	0.52	0.55	0.57	0.59	0.62
$\Omega[2,3]$	-0.20	-0.16	-0.12	-0.09	-0.04
$\Omega[2,4]$	-0.21	-0.16	-0.12	-0.08	-0.03
$\Omega[2,5]$	0.07	0.13	0.17	0.21	0.26
$\Omega[2,6]$	-0.05	-0.00	0.04	0.07	0.13
$\Omega[3,4]$	0.41	0.45	0.48	0.50	0.53
$\Omega[3,5]$	-0.00	0.04	0.07	0.10	0.14
$\Omega[3,6]$	-0.09	-0.05	-0.02	0.01	0.05
$\Omega[4,5]$	-0.58	-0.54	-0.51	-0.48	-0.43
$\Omega[4,6]$	-0.24	-0.20	-0.17	-0.14	-0.10
$\Omega[5,6]$	-0.27	-0.22	-0.19	-0.16	-0.11

Table 17: Posterior quantiles for noise parameters.

F Selected additional tables and figures

Tables 18–21 below summarize the posterior correlations across estimated parameters by couples' labor market status. The results indicate that males' and females' log wage rates are positively correlated if at least one spouse is employed. The correlation coefficients range from 0.12 to 0.19. Males' and females' α are only weakly correlated. They are positively correlated if the female is employed irrespective of her partner's labor market state. They are negatively correlated otherwise. For each gender, the own α is negatively correlated with the log own wage rate.

Let us next consider the negative bias associated with females' own-wage elasticity when wages are aggregated.[34] Wage aggregation induces some low-wage females to enter employment, thereby changing their couple's status from NN to NE, or from EN to EE. Each of these switches raises market hours and reduces females' own-wage elasticity. The plot in the panel of the bottom row indicates that these are females with a high-wage male partner. Note that there is a small counteracting effect caused by some high-wage females in NE couples who reduce their hours in reaction to wage-aggregation, inducing their male partner to enter employment.

In sum, females react similar to males in that their own-wage elasticity tends to decrease for low-wage earners with the decrease rising in their partners' wage rate. The elasticity increases for high-wage females, and the increase is strongest if the male partners' wage rate is low. Like for men, the contribution to the bias in females' own-wage elasticity is larger when couples are unequal with respect to their wages. In contrast to men, the first effect dominates the second which explains the negative bias.

Next, let us focus on the cross-wage elasticity of men. Wage aggregation lets this negative elasticity decrease further. This decrease is concentrated among men in dual-earner couples who are partnered with low-wage females. These are men with an above average wage rate who reduce their market hours following wage aggregation. Their reaction dominates the aggregation bias, since it outweighs a slight rise in the elasticity stemming from low-wage males who increase their hours, particularly if partnered with a high-wage female.

We briefly discuss Figure 18. First, let us focus on the cross-wage elasticity of men. Preference aggregation lets this negative elasticity decrease by 4 percentage points.[35] This decrease is concentrated among men in dual-earner couples. These are men with a very high α. The size of their market hours' reduction declines in their female partner's α, because that way, males can partially offset their partners' hours reduction when preferences are aggregated. Overall it is high α males coupled with high α females who matter most for generating the decline in market hours that translates into the observed decline in men's cross-wage elasticity.

For females, preference aggregation lets their own-wage elasticity rise by 29 percentage points. When subsequently also aggregating wages, this elasticity rises once more by the same extent. Who are the females who contribute to a rise in the elasticity when only preferences are aggregated? According to the plots in the right column of Figure 18 these are women in dual-career couples whose α lies above the median. Preference aggregation induces some of them to withdraw from employment altogether, while others decrease their market hours, thereby generating a strong rise

[34] The right column of Fig. 17 depicts the decomposition.

[35] The left column in Figure 18 illustrates the decompositions.

	α_f	β_m	β_f	$\log(w_m)$	$\log(w_f)$
α_m	0.04	-0.43	-0.16	-0.50	0.34
α_f		-0.09	-0.49	0.28	-0.50
β_m			0.37	0.04	-0.09
β_f				0.02	0.03
$\log(w_m)$					0.12

Table 18: Posterior correlations across couple parameters, EE couples.

	α_f	β_m	β_f	$\log(w_m)$	$\log(w_f)$
α_m	-0.06	-0.38	-0.03	-0.36	0.35
α_f		-0.10	-0.43	0.43	-0.53
β_m			0.31	-0.03	-0.01
β_f				0.06	0.19
$\log(w_m)$					0.14

Table 19: Posterior correlations across couple parameters, EN couples.

in their own-wage elasticity.[36] The additional adjustment that takes place when subsequently also aggregating wages can be inferred from the right panel of Figure 19. The induced strong rise in females' own-wage elasticity is concentrated among women with a below average α and an above average wage rate; these women reduce their market hours upon aggregation.

When only preferences are aggregated, it is females whose α_f lies in the third quartile whose induced reduction in market hours drives the intermittent rise in females' own-wage elasticity. However, when also aggregating wages, the right panel of Figure 19 suggests that it is females with a low α_f and a low wage rate w_f who not only increase market hours in reaction to preference aggregation, but who further increase hours if wages are aggregated. These females' reaction dominates when wages are aggregated and it also dominates the overall change, causing a significant reduction in the own-wage elasticity. Unlike for males, α_f and w_f are only weakly negatively correlated in our cross-sectional distribution (see Tables 18 to 21 and/or 16). Male cross-wage elasticities decrease by an additional 23 percentage points when aggregating wages in addition to preferences. Preference aggregation only leads to a small decline in this elasticity, and the decline is concentrated among males in dual-earner couples whose α is very high. When adding wage aggregation to this, we observe in the left panel of Figure 19 that this decline is concentrated among men whose female partners' wage rates lie in the lowest quartile. Those men tend to weakly decrease market hours upon total parameter aggregation.

[36] The fact that these females tend to have partners with α above the median seems little relevant, since those preference parameters are barely correlated across gender.

	α_f	β_m	β_f	$\log(w_m)$	$\log(w_f)$
α_m	0.12	−0.46	−0.25	−0.58	0.31
α_f		−0.15	−0.59	0.23	−0.35
β_m			0.28	0.03	−0.07
β_f				0.04	0.03
$\log(w_m)$					0.19

Table 20: Posterior correlations across couple parameters, NE couples.

	α_f	β_m	β_f	$\log(w_m)$	$\log(w_f)$
α_m	−0.02	−0.32	−0.11	−0.63	0.35
α_f		−0.05	−0.41	0.29	−0.56
β_m			0.24	−0.03	0.01
β_f				0.08	0.02
$\log(w_m)$					−0.10

Table 21: Posterior correlations across couple parameters, NN couples.

(a) Partition by estimated male and female α quantiles.

	$\alpha_m\ q_1$			$\alpha_m\ q_2$			$\alpha_m\ q_3$			$\alpha_m\ q_4$		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
$\alpha_f\ q_4$	0.04	0.21	−0.85	0.05	0.32	−1.31	0.07	0.43	−1.31	0.10	0.52	−1.09
$\alpha_f\ q_3$	0.04	0.21	−0.65	0.06	0.38	−1.13	0.07	0.51	−1.22	0.08	0.59	−1.07
$\alpha_f\ q_2$	0.06	0.22	−0.51	0.06	0.39	−0.91	0.06	0.54	−1.01	0.06	0.64	−0.92
$\alpha_f\ q_1$	0.10	0.18	−0.24	0.07	0.34	−0.46	0.05	0.48	−0.63	0.04	0.65	−0.58

(b) Partition by estimated male and female β quantiles.

	$\beta_m\ q_1$			$\beta_m\ q_2$			$\beta_m\ q_3$			$\beta_m\ q_4$		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
$\beta_f\ q_4$	0.04	0.14	−0.21	0.05	0.20	−0.39	0.06	0.25	−0.54	0.07	0.33	−0.73
$\beta_f\ q_3$	0.05	0.26	−0.55	0.06	0.35	−0.83	0.06	0.41	−0.97	0.06	0.46	−0.93
$\beta_f\ q_2$	0.06	0.39	−0.90	0.07	0.47	−1.10	0.07	0.51	−1.12	0.06	0.49	−0.88
$\beta_f\ q_1$	0.11	0.53	−1.11	0.08	0.55	−1.15	0.07	0.54	−1.10	0.05	0.46	−0.77

(c) Partition by estimated male α and (ex ante) wage quantiles.

	$w_m\ q_1$			$w_m\ q_2$			$w_m\ q_3$			$w_m\ q_4$		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
$\alpha_m\ q_4$	0.12	0.65	−0.88	0.09	0.60	−1.00	0.03	0.44	−1.13	0.03	0.41	−1.20
$\alpha_m\ q_3$	0.06	0.59	−0.78	0.09	0.53	−1.08	0.07	0.42	−1.25	0.04	0.36	−1.27
$\alpha_m\ q_2$	0.04	0.42	−0.44	0.07	0.41	−0.93	0.07	0.35	−1.08	0.06	0.27	−1.11
$\alpha_m\ q_1$	0.06	0.17	−0.10	0.05	0.24	−0.46	0.06	0.23	−0.65	0.06	0.17	−0.67

Table 22: Decompositions of elasticities to a male wage increase for the estimated model.

(a) Partition by estimated male and female α quantiles.

	α_m q_1			α_m q_2			α_m q_3			α_m q_4		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
α_f q_4	0.04	-0.17	1.05	0.05	-0.30	1.38	0.07	-0.42	1.32	0.10	-0.50	1.12
α_f q_3	0.04	-0.18	0.84	0.06	-0.37	1.20	0.07	-0.50	1.23	0.08	-0.58	1.11
α_f q_2	0.06	-0.17	0.67	0.06	-0.36	1.02	0.06	-0.51	1.07	0.06	-0.63	0.97
α_f q_1	0.10	-0.11	0.36	0.07	-0.27	0.60	0.05	-0.41	0.73	0.04	-0.60	0.68

(b) Partition by estimated male and female β quantiles.

	β_m q_1			β_m q_2			β_m q_3			β_m q_4		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
β_f q_4	0.04	-0.09	0.34	0.05	-0.15	0.52	0.06	-0.22	0.68	0.07	-0.29	0.86
β_f q_3	0.05	-0.21	0.71	0.06	-0.32	0.96	0.06	-0.39	1.07	0.06	-0.41	1.02
β_f q_2	0.06	-0.37	1.02	0.07	-0.46	1.16	0.07	-0.49	1.16	0.06	-0.42	0.96
β_f q_1	0.11	-0.53	1.13	0.08	-0.54	1.16	0.07	-0.51	1.13	0.05	-0.37	0.87

(c) Partition by estimated female α and (ex ante) wage quantiles.

	w_f q_1			w_f q_2			w_f q_3			w_f q_4		
	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$	$\hat{f}$	$\bar{\varepsilon}_m$	$\bar{\varepsilon}_f$
α_f q_4	0.08	-0.17	1.10	0.08	-0.41	1.46	0.07	-0.49	1.22	0.04	-0.59	0.98
α_f q_3	0.05	-0.06	0.46	0.06	-0.43	1.46	0.07	-0.54	1.33	0.06	-0.67	1.09
α_f q_2	0.06	-0.05	0.26	0.05	-0.29	1.07	0.07	-0.58	1.29	0.06	-0.72	1.10
α_f q_1	0.07	-0.02	0.09	0.06	-0.10	0.39	0.06	-0.40	0.80	0.07	-0.63	0.92

Table 23: Decompositions of elasticities to a female wage increase for the estimated model.

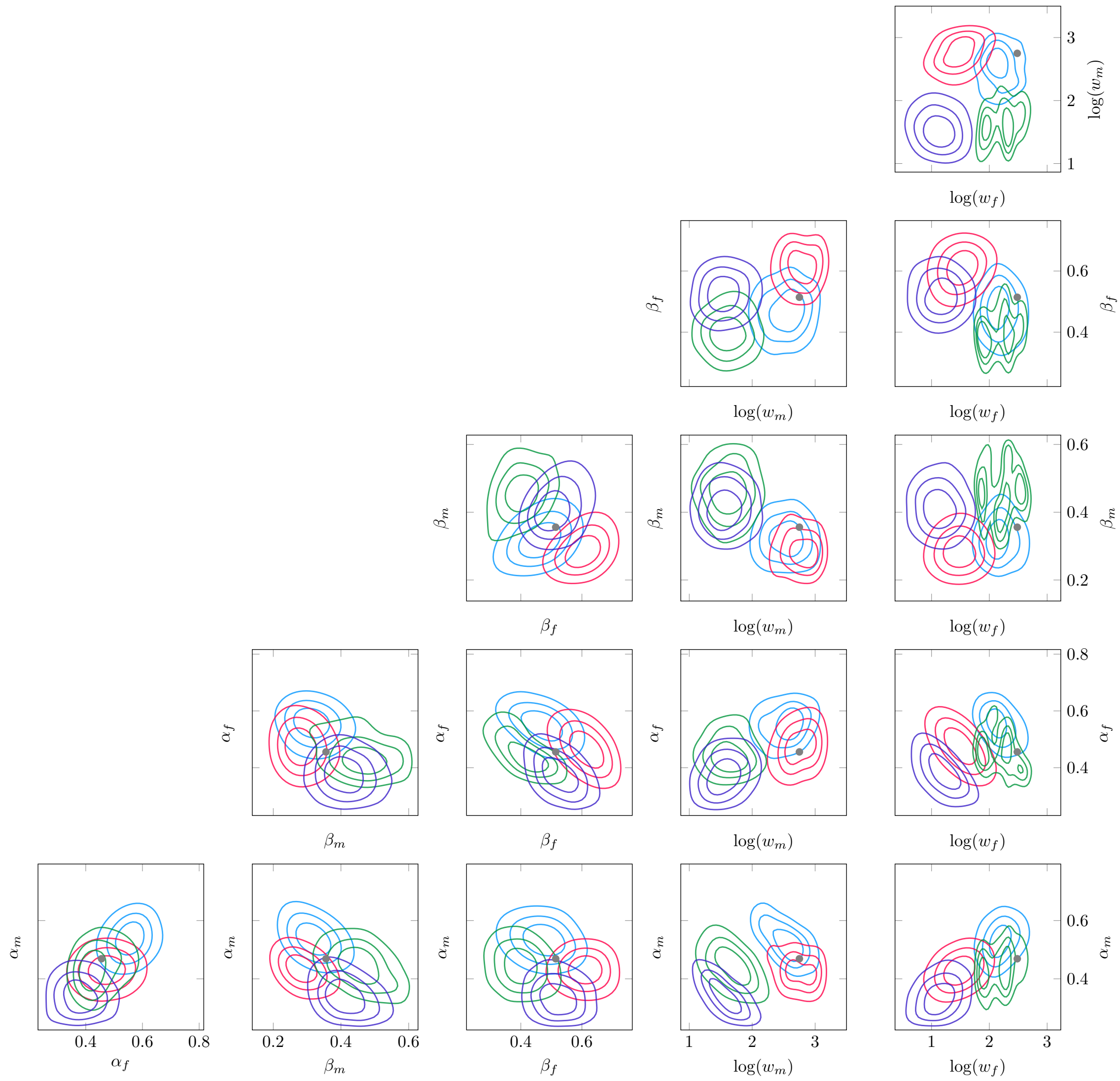

Figure 16: Cross-sectional parameter estimates. Contour plots for highest posterior density regions (75%, 50%, 25%). Color legend: EE, EN, NE, NN; ● shows the representative couple. Contours are calculated using kernel density smoothing.

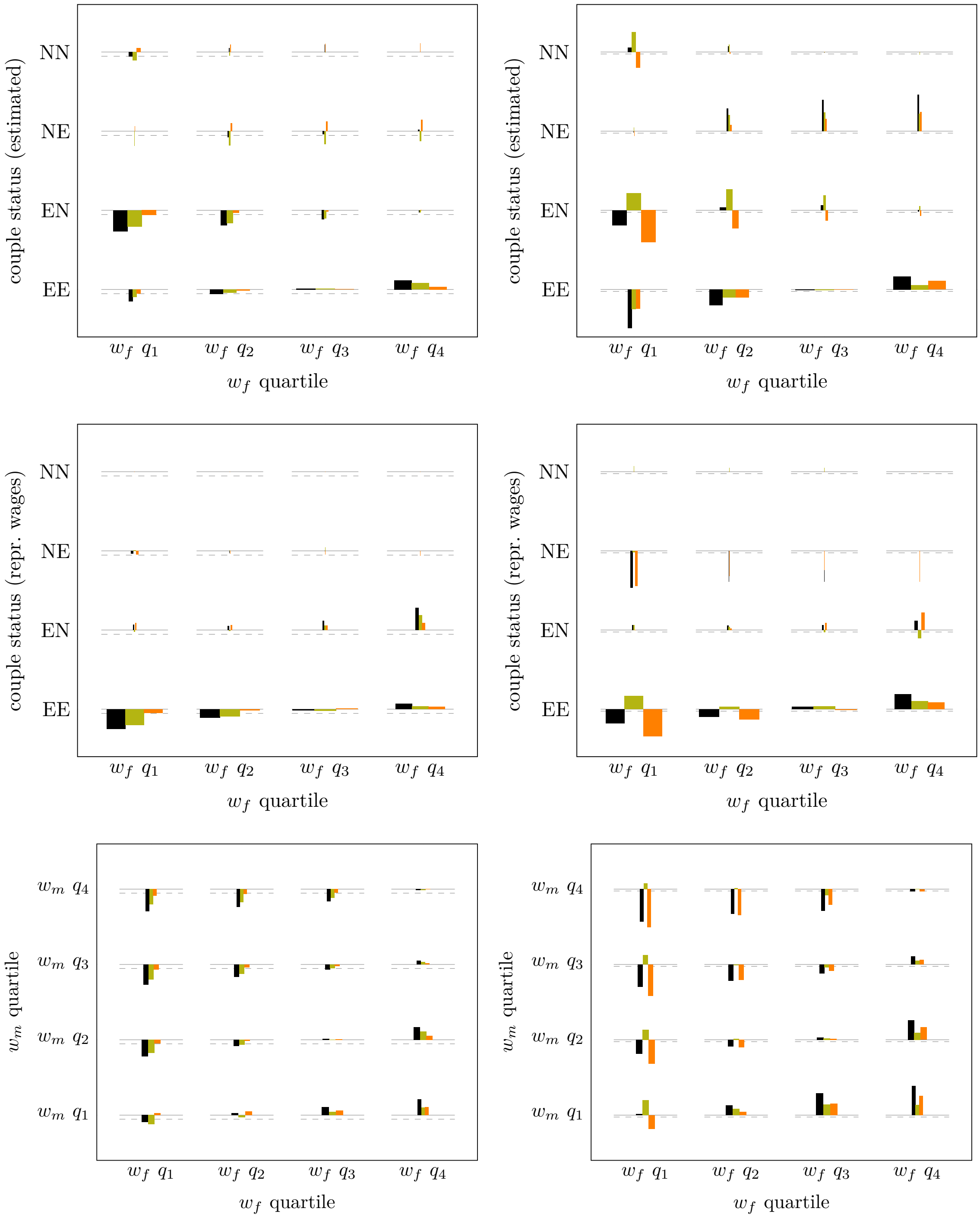

Figure 17: Decomposition of aggregation bias between estimated model and wage aggregation for male cross-wage elasticities (left) and female own-wage elasticities (right). Color legend: total, $\hat{\Delta}$, $\hat{n}$, - - - difference in aggregate elasticity, —— 0; decomposition figure scales are consistent, and thus comparable throughout the paper.

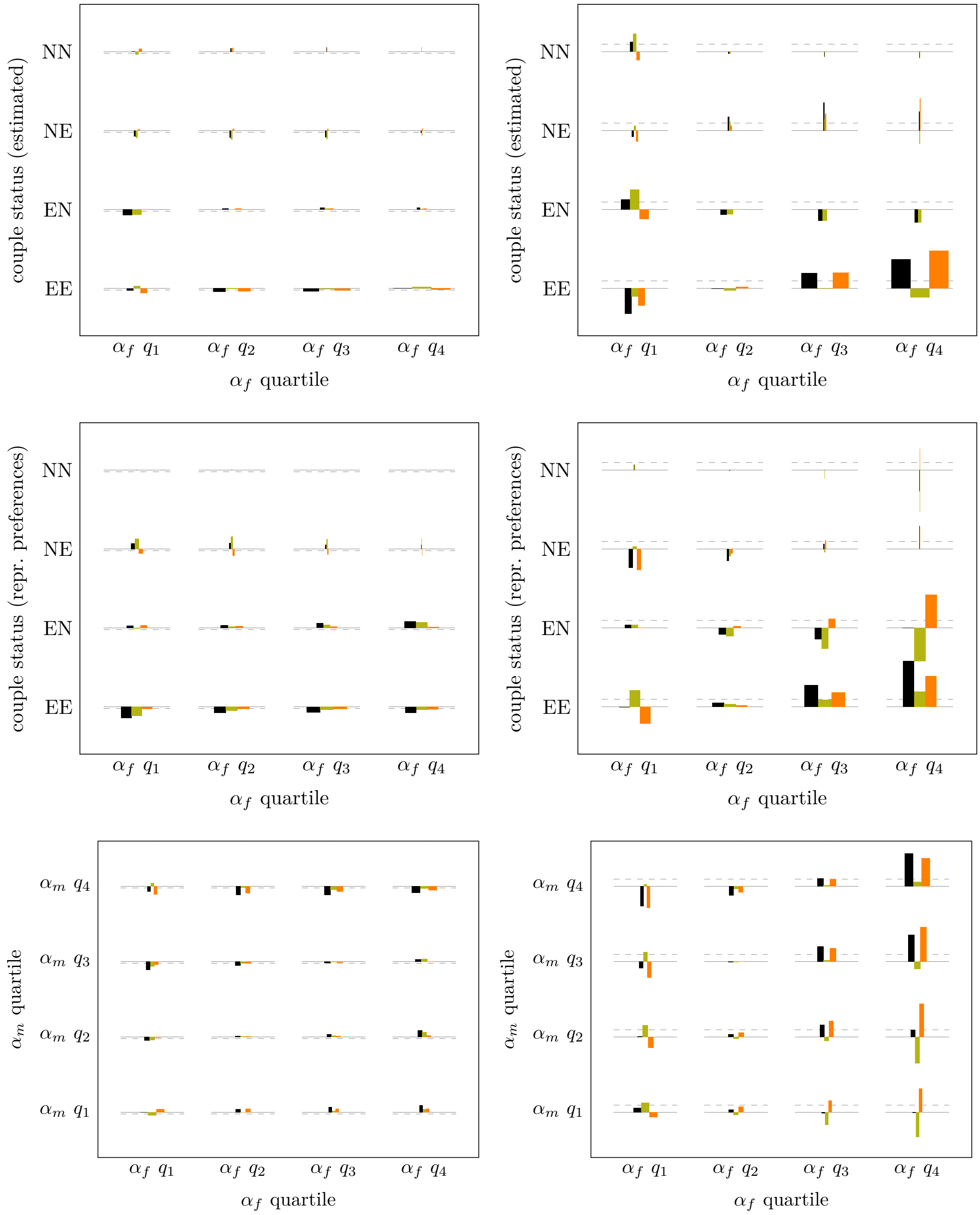

Figure 18: Decomposition of aggregation bias between estimated model and preference aggregation for male cross-wage elasticities (left) and female own-wage elasticities (right). Color legend: total, $\hat{\Delta}$, $\hat{n}$, - - - difference in aggregate elasticity, —— 0; decomposition figure scales are consistent, and thus comparable throughout the paper.

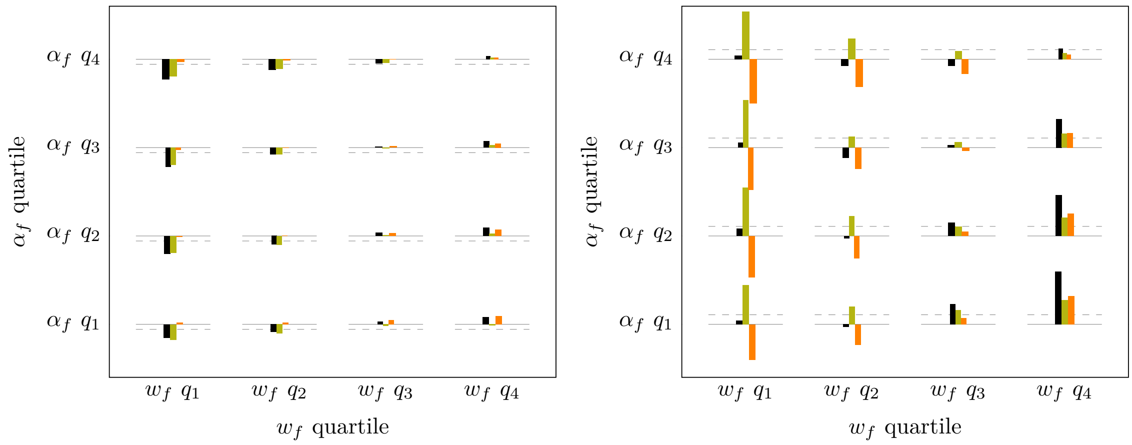

Figure 19: Decomposition of aggregation bias between preference aggregation and preference and wage aggregation for males' cross-wage elasticities (left) and females' own-wage elasticities (right). Color legend: ▬ total, ▬ $\hat{\Delta}$, ▬ $\hat{n}$, - - - difference in aggregate elasticity, —— 0; decomposition figure scales are consistent, and thus comparable throughout the paper.

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	0.056	0.081		
representative wage	0.049	0.053	−12%	−34%
representative preferences	0.078	0.142	40%	76%
representative wages & preferences	0.052	0.100	−7%	24%
homogeneous couple	0.069	0.069	24%	−14%

Table 24: Responses of hours to a 10% increase in *both* wages (elasticity) with $\gamma = 0.7$.

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	0.400	−0.963		
representative wage	0.517	−0.940	29%	−2%
representative preferences	0.480	−1.162	20%	21%
representative wages & preferences	0.630	−1.682	57%	75%

Table 25: Responses of hours to a 10% *male* wage increase (elasticity) with $\gamma = 0.7$.

exercise	hours elasticity male	hours elasticity female	change male	change female
estimated	−0.372	1.033		
representative wage	−0.523	0.957	40%	−7%
representative preferences	−0.447	1.360	20%	32%
representative wages & preferences	−0.636	1.633	71%	58%

Table 26: Responses of hours to a 10% *female* wage increase (elasticity) with $\gamma = 0.7$.

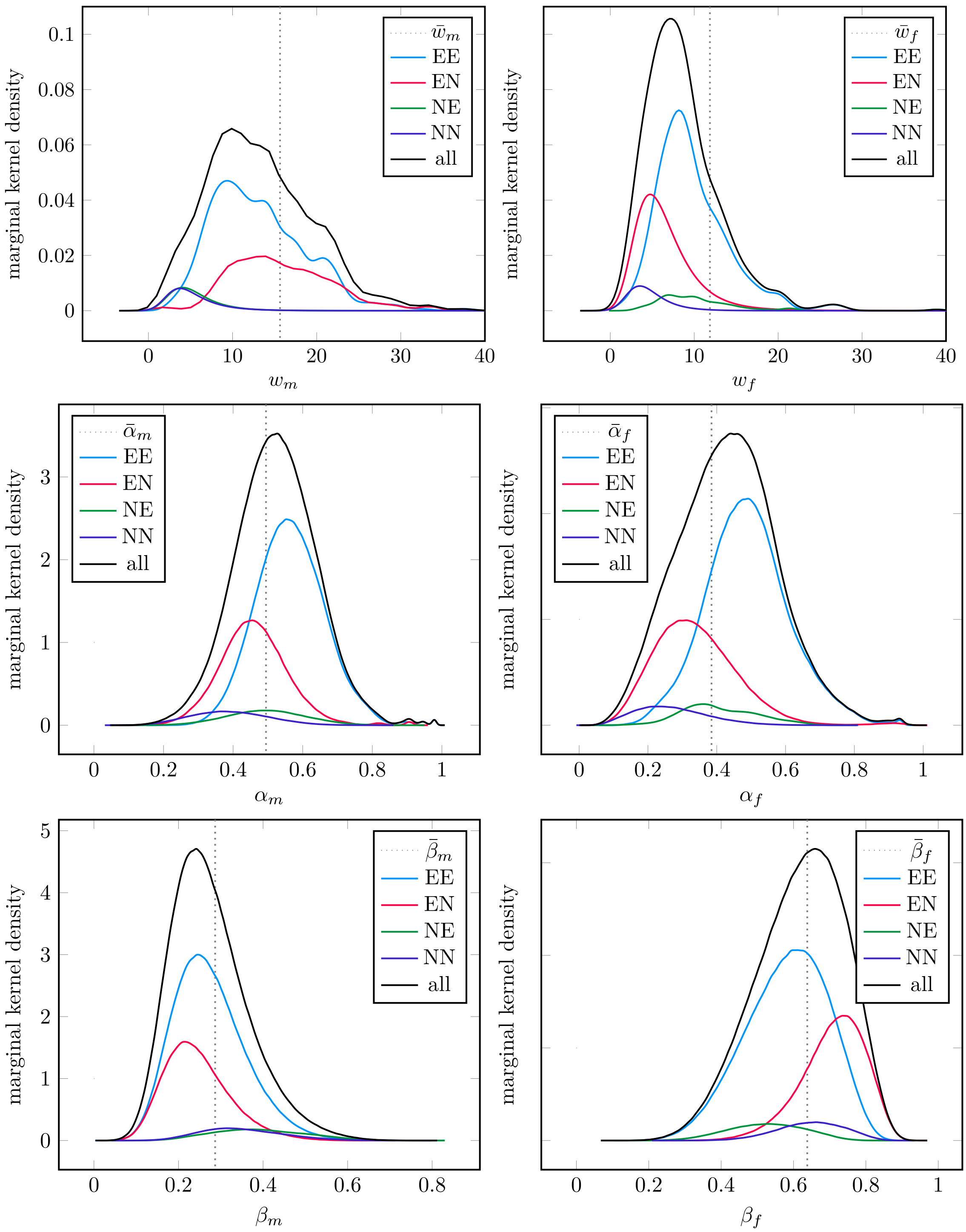

Figure 20: Cross-sectional marginal posterior densities with $\gamma = 0.7$.