Couples' Time-Use and Aggregate Outcomes: Evidence from a Structural Model

Almut Balleer[*], Monika Merz[†], Tamás K. Papp[‡]

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Abstract

We analyze the economic determinants of couples' decisions to allocate their available time across market work, home work, and leisure using the German Time-Use Surveys of 2001/02 and 2012/13. These data allow identifying actual couples who can be married or cohabiting. Specifically, we use Bayesian indirect inference to estimate a static model of couples' time-allocation decisions allowing for 'no market work' as a possible outcome. The model features intra-household and inter-household heterogeneity. Partners differ in their tastes for purchased consumption goods and non-market goods and activities as well as in their offered or earned wage rate. We use the estimated model as a lab for counterfactual exercises in the cross-section. We find own-wage and cross-wage elasticities of hours worked to be larger for females than males, and that the extensive margin of adjusting employment is quantitatively more important than the intensive margin. We also aggregate preferences and wages by gender and compare outcomes for a stand-in couple with those from heterogeneous couples. We find that preferences rather than wages are the prime determinant of labor-leisure choices in the aggregate, especially for females.

JEL-Classification: D12, D13, J22.

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[*]RWTH Aachen, IIES Stockholm and CEPR; Email:almut.balleer@iies.su.se

[†]University of Vienna, CEPR, and IZA;Email:monika.merz@univie.ac.at

[‡]Institute for Advanced Studies, Vienna; Email:tpapp@ihs.ac.at

1 Introduction

Women and men in partnerships constitute more than two-thirds of the working-age population in most countries in Continental Europe. Moreover, men in partnerships supply the lion's share of total hours worked by men in the market. Like in the US, women in partnerships in many Western European countries have steadily and significantly increased their labor force participation, albeit at a later time period.[1] Contrary to the US, a significant share of them still work fewer hours in the market than their male partners and instead pursue more housework or enjoy leisure. Those aggregate observations are of interest from a macroeconomic perspective, because they constitute a significant part of total labor supply or home work in an economy. However, they disguise a huge amount of diversity in the underlying time allocation choices of men and women in partnerships and the fact that their choices typically are not independent from each other. Therefore, understanding what determines couples' time-allocation decisions most likely matters for understanding observed differences in total market hours worked over time or across countries.

This paper formulates a static model of couples' time-allocation decisions when each partner can allocate the available time between market work, housework, and leisure. It uses the German Time-Use Surveys (TUS) of 2001/02 and 2012/13 for estimating the structural model parameters. The paper's focus is on the quantitative implications that varying degrees of heterogeneity in a partner's tastes and wage rates as well as aggregation have for the dynamics of total hours worked, homework, and leisure. It thus contributes to the growing literature on the role of families or couples in macroeconomics.[2]

The German TUS has two distinct features that we exploit for our analysis. It contains detailed information on an individual's actual time-use including the distinction between a particular activity in a broadly or a narrowly defined sense. Moreover, the data report information on real couples which can be married or cohabiting.[3] The data also contain relevant individual characteristics such as age, and the highest education level achieved together with monthly net earnings and usual hours worked if employed. At the household level, they report non-labor income and the number and age of children living in the household. Even though the time-use data is available for two cross-sections only, when

[1] McGrattan and Rogerson (2004) document these trends for the United States, and Merz (2010) does the same for Germany.

[2] Doepke and Tertilt (2016) nicely summarize the current state of this literature.

[3] Detailed information on individual time use matters, e.g. when trying to disentangle leisure from partly overlapping activities such as childcare.

combined with our model it can help shed light on the role that preferences or wages play for the dynamics of the implied aggregates.

Data availability dictates much of our modeling choice. We choose a static environment, since the time-use evidence originates from two separate cross-sections, and we cannot follow the individuals or households over the different surveys. We allow for intra-household and inter-household heterogeneity. To simplify language we use partners and spouses interchangeably irrespective of the marital status. We commonly refer to the female partner as wife and to the male partner as husband. Spouses may differ in their tastes for purchased consumption goods and non-market goods and activities as well as in their offered or earned wage rate, but they share their joint income which consists of total earnings plus non-labor income. Of course, tastes, wage rates and non-labor income vary across couples.

In order to explore the importance of cooperation among spouses, we pursue two alternative model specifications that differ in whether or not the equilibrium allocation is unique and efficient. Each specification allows for 'no market work' of either partner as a possible outcome. In the first specification, we let each partner choose how to allocate the available time in order to maximize utility, given the other partner's decisions.[4] The resulting equilibrium is typically inefficient, but unique which makes it particularly suitable for estimation. It corresponds to an important benchmark, given that the associated utility levels represent each partner's threat point that can help to support a cooperative outcome. Alternatively, we let a social planner choose the couples' time allocation in order to maximize the weighted product of their individual utilities. The outcome is efficient, but hinges on the exact utility weights.

We estimate our model using Bayesian indirect likelihood methods. For each set of parameters, we simulate outcomes from the structural model. Then we estimate an auxiliary model, modeling the six-element vector of incomes, work- and leisure hours for both members of each couple *jointly* using a vector-valued linear regression, from which the coefficient and variance matrices constitute our indirect parameters. We construct a likelihood using the method of Gallant and McCulloch (2009), and form a posterior using standard weak priors. We sample from the posterior using a recent improvement of the No-U-turn sampler of Hoffman and Gelman (2014), as described in Betancourt (2017). For this we need the

[4]This individual time allocation decision can alternatively be interpreted as each partner deciding on how much time to voluntarily contribute to the 'production' of the two types of consumption goods each of which is a public good.

gradient of the posterior, which we obtain using automatic differentiation.[5]

Given the many dimensions of heterogeneity and the fact that we can estimate the distributions of taste parameters and wage rates, our model provides a lab for addressing detailed questions related to time allocation of spouses. We use it for two different types of analysis. First, we do counterfactual exercises in the cross-section. We successively change the offered wage of men only, of females only, and of both spouses and quantify the reaction of spouses' time-allocation in general and their hours worked in particular. This exercise not only delivers the mean of spouses' own-wage elasticity of hours worked as well as that of the corresponding cross-wage elasticities. It also sheds light on the composition of these elasticities by indicating how much of the overall adjustment in hours worked occurs because of a partner moving from non-employment into employment as opposed to adjusting hours while remaining employed. Our results show that own-wage and cross-wage elasticities of hours worked are larger for females than for males. Moreover, most of the changes in hours worked result from adjustment along the extensive rather than the intensive margin.

Second, we aggregate by successively reducing the amount of heterogeneity in our model. We depart from our setup with couples where we allow spouses to differ in tastes and wage rates. We abandon the inter-household heterogeneity and assign all wives the cross-sectional mean values of taste parameters and wages; we treat husbands analogously. This yields a representative household with a stand-in wife and husband.[6] When comparing the implied time-allocation for husbands and wives, we find that preferences rather than wages are the prime determinant of labor-leisure choices in the aggregate, especially for females.

The remainder of the paper is structured as follows. Section 2 provides a brief overview of the related literature. Section 3 introduces details of the German Time-Use Survey. Section 4 introduces the model setup, while Section 5 lays out the estimation strategy. Section 6 discusses the results, and Section 7 concludes.[7]

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[5]To the best of our knowledge, combining indirect inference with Hamiltonian Monte Carlo methods is a novel contribution of this paper, which provides almost perfect mixing and thus very fast runtimes for the sampler, making it as efficient as methods based on the exact likelihood.

[6]Ramey and Francis (2009) explicitly distinguish between a representative household and a representative agent when studying determinants of long-run trends in market work and leisure in the US.

[7]Code for estimation is available at . Even though the database does not have open access, this repository includes routines for simulating data, allowing others to assess and replicate our results more easily.

2 Related Literature

We are not the first ones to study labor supply of women and men in the broader context of time-allocation within a household model. The unitary approach to modeling household behavior dominates much of the literature on time-use in a macroeconomic context. It can empirically be justified by the availability of highly aggregate data on market work, or home work. It takes a household as the unit of analysis and implicitly assumes that all household members have identical preferences and share the same objective and constraints.[8] This approach underlies Prescott (2004) path-breaking study of the role that labor income taxes played in generating opposite long-run trends of market hours worked and leisure in the US and in selected European countries. It has been used in many subsequent studies of time-allocation in a country-specific context. Rogerson (2008) allows the representative household to allocate available time between market work, leisure and housework when exploring the role of labor income taxes and labor productivity for sectoral reallocation between manufacturing and services in the U.S. and European countries. Duernecker and Herrendorf (2015) as well as Ragan (2013) use the same approach for studying public transfers, in addition to labor income taxes, in order to understand why homework in much of Scandinavia and France is relatively low compared to the US. More recently, Ngai and Petrongolo (2016) and Ngai and Boppart (2016) have used the same environment for exploring the link between gender differences in the allocation of market work and home work and gender-specific wage differences, or rising income inequality and long-run trends in leisure, respectively.

The desire to better understand the determinants of a household's internal decision-making process and the implied intra-household distribution of material well-being in the form of leisure, consumption or welfare triggered the formulation of so-called household models.[9] This class of models explicitly considers individual members with their respective objectives and constraints and allows for various degrees of interaction between them. They comprise cooperative as well as non-cooperative versions.[10] Neither type specifies the intra-household bargaining process between the household members, but they generate

[8] Already Samuelson (1956) questioned the plausibility of a household's utility function, stressing that is was resting on very strong assumptions.

[9] The contribution of Becker (1981) laid the foundation for this development. It was facilitated by the increased availability of micro level data on time-use, or income.

[10] Cooperative models that explicitly consider variations of the internal distribution of 'power' are also known as collective household models. They were pioneered by Chiappori (1988), Apps and Rees (1988), and Browning and Chiappori (1998).

allocations that can be interpreted as if they had bargained with each other. They differ in that 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.

Cooperative household models typically generate a contract curve which corresponds to a continuum of Pareto optimal allocations. In order to single out one particular allocation, a sharing rule needs to be imposed that specifies how total household income is split between the members.[11] Cooperation can be supported by alternative outside options to which spouses can recede in case of disagreement. McElroy and Horney (1981) and Manser and Brown (1980) are early examples of divorce-threat cooperative bargaining models that take divorce or remaining single as relevant outside option. But of course, following John Nash's logic who argued that any cooperative game should be preceded by a non-cooperative one in order to establish outside options for the parties involved, non-cooperation while maintaining the relationship is a legitimate alternative.

Models that focus on the behavior of couples who play a non-cooperative equilibrium pursue this latter route. Those couples can be seen as spouses who have moved well beyond their honeymoon and who act strategically given their spouses' behavior. Although the resulting equilibrium typically is inefficient, it is unique — a feature which is essential for empirical work. This unique equilibrium generates an indirect utility level for each partner which corresponds to the respective threat point and therefore constitutes an important benchmark for any analysis that assumes cooperative behavior.[12]

Our analysis departs from this non-cooperative static approach. We formulate a model of spouses' endogenous time-allocation decisions allowing them to optimally choose between market work, housework, and leisure in order to maximize their utility while taking their spouse's decisions as given. We supplement the non-cooperative approach by a social

[11] Much of this literature has dealt with the conditions under which such a sharing rule exists and how to determine it. Lise and Yamada (2015) use a dynamic model version and combine it with individual data on leisure and consumption expenditure in order to identify males' and females' share of household income. Theloudis (2015) integrates a cooperative setting into a life-cycle model of time allocation and consumption behavior in order to explore the role that the closing of the gender-wage gap has had for the amount of homework and market work supplied by women and men in the U.S.

[12] Browning, Chiappori, and Lechene (2010) also stress this fact. Doepke and Tertilt (2014) embed home production and gender-specific wage differences into this setting when investigating the role of public transfers targeted at wives rather than husbands within a family for the economic development of a country. Earlier examples of non-cooperative household models at work include Bourguinon (1984), Lundberg and Pollak (1994), and Konrad and Lommerud (1995) and Del Boca and Flinn (1995) and Del Boca and Flinn (2012).

planner's version in order to explore the importance of cooperation among partners for their time use decisions. Both model versions allow for endogenous corners in market work as a possible outcome. They also capture intra-household as well as inter-household heterogeneity in preferences and wage rates. Our work is empirically motivated. We use actual time-use data of real spouses to estimate the distributions of individual taste parameters and wage rates. We use the estimated model for a battery of counterfactual exercises in the cross-section which — among other things — render own-wage and cross-wage elasticities of hours worked by gender. Our work thus also relates to the vast literature on empirical estimates of labor supply elasticities much of which Blundell and MaCurdy (1999) summarize. We aggregate by successively reducing the amount of heterogeneity in that we replace individual specific preference parameters and wage rates by their respective cross-sectional mean for men or women. We can thus compare the predicted time-allocation for a stand-in household to that of heterogeneous households and thereby contribute to the growing literature that explores the role of families for macroeconomic dynamics. Doepke and Tertilt (2016) summarize the current state of this literature.

3 The German Time-Use Survey

We use two waves of cross-sectional data from the German Time use Survey provided by the Federal statistical office (Destatis): 2001/2002 and 2012/2013.[13] The original data consists of three parts that are merged for our baseline dataset: The individual time-use dimension, personal socio-economic information and household information. With respect to the time-use data, we aggregate up the information from the minute-by-minute diaries into daily aggregates for different categories. Observations include up to three days per person including both weekdays and weekends. Via the household dimension, we can identify couples and have information about other persons living in the household and their respective use of time.[14]

We compute three categories of time use: market work, home production and leisure. Core market work consists of time spent in the main or secondary job as well as qualification on the job. Total market work then adds other things related to the job, searching for a job,

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

[14]There exists a third wave 1991/1992 which we cannot use, since it misses information about hours and income necessary for our model estimation.

breaks and commuting time. Core home production encompasses meals and various kinds of maintenance in the home. Total home production adds shopping, gardening, construction and childcare. We follow Aguiar and Hurst (2007) in the definition of market work and home production with one exception: care other than child care (i.e. of adults) is included in home production. Daily leisure is defined as 24 hours minus 8 hours for sleep and personal care minus total market work minus total home production. We exclude households with kids under 6 years old, since they affect working hours of parents, especially women, in a particular way which we do not explicitly describe in our model. We consider only couples in which both partners are between 24 and 64 years old (in the labor force). We consider only weekdays.

Table 3 shows the average daily time use for four different couple types: both partners work, only the man works, only the woman works and no partner works. In addition, we distinguish between couples with and without kids. 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 one partner works, the other works more at home and enjoys more leisure. If the women is the only wage-earner, her market hours are still lower and home production higher compared to her male counterpart. This pattern persists also if none of the partners work. Childcare is negligible if kids are older than 6 years old. The bottom of the table shows the average time-use of men and women in the sample. One may view this as a synthetic couple in case no further information about the actual partners' choice is available. One can see that this average is not representative of any of the actual couples' choices in the sample. Table 9 in the Appendix shows the respective daily time use in the 2012/2013 wave. Albeit a bit of convergence between the men and women in the household in terms of both market hours and home production, a similar pattern of time use as in the early wave can be observed.

Figure 7 in the Appendix plots the age profiles of time-use for men and women. For men, time-use is constant between the age of 30 and 50. Beyond 50, market work decreases, while home production and leisure increase. For women, home production is roughly constant, while market work decreases and leisure increases during a life-time.

In order to obtain individual income, we construct the wage from the main and, possibly, secondary job (when only bracketed information is available, we use the mid-point of the bracket as an approximation for the wage). We then compute the hourly wage as the wage from the main and, possibly, secondary job and divide by usual hours worked. We discard

Table 1: Average daily time use 2001/2002

couple type		market work				home production										leisure	
		total		core		total		core		shop		other		child			
		h	m	h	m	h	m	h	m	h	m	h	m	h	m	h	m
both work	man	7	58	6	50	1	59	0	36	0	42	1	55	0	1	6	3
no kids	woman	6	26	5	34	3	26	1	52	1	8	3	18	0	2	6	8
both work	man	9	2	7	49	1	51	0	31	0	34	1	36	0	13	5	7
kids	woman	5	9	4	30	4	55	2	39	1	10	4	9	0	38	5	56
one works	man (works)	7	5	5	56	1	50	0	37	0	38	1	45	0	2	7	5
no kids	woman	0	5	0	3	6	6	3	50	1	23	5	56	0	4	9	50
	man	0	2	0	0	5	15	1	57	1	26	5	7	0	3	10	43
	woman (works)	5	15	4	35	3	46	2	5	1	6	3	33	0	4	6	59
one works	man (works)	8	36	7	34	1	41	0	26	0	33	1	23	0	16	5	42
kids	woman	0	11	0	3	7	51	4	31	1	33	6	46	0	58	7	58
	man	0	18	0	2	5	8	1	41	1	36	4	35	0	18	10	35
	woman (works)	5	42	5	2	3	55	2	8	1	12	3	34	0	17	6	23
nobody works	man	0	2	0	0	4	39	1	18	1	35	4	35	0	0	11	19
no kids	woman	0	2	0	0	6	15	3	41	1	37	6	0	0	5	9	43
nobody works	man	0	9	0	5	5	1	1	21	1	31	4	43	0	12	10	50
kids	woman	0	7	0	4	6	29	3	55	1	34	6	1	0	21	9	23
synthetic couple	man	6	12	7	11	2	23	0	42	0	45	2	9	0	10	6	27
	woman	3	23	3	54	5	14	2	56	1	16	4	38	0	29	6	52

Notes: Figures show daily averages of various time use aggregates in hours (h) and minutes (m). In home production, shop denotes shopping, other denotes gardening and construction, and child denotes childcare. The synthetic couple shows the average time-use of males and females irrespective of their couple status.

unreasonable working hours: more than 14 hours of daily core market work and more than 16 hours in total market work. We also discard unreasonably high hourly wages (above 200 Euros). We obtain total household income from the survey and compute non-wage income as the difference between the sum of the individual wage incomes and total household income. All wages and income are net of taxes.

For the 2001/2002 wave, table 8 in the Appendix shows the number of observations, labor and non-labor income of our four different couple types. In general, the variation in wages and income within couple types is high. Most of our 1916 couples are couples in which both partners work. Regardless of the couple type, women earn substantially lower market wages than men. Couples in which no partner or only the woman works have substantially higher non-labor income. Table 11 in the Appendix shows the main source of income for different household types. When both partners or the man in the household works, the main source of income is wage income. In case no partner works or the woman works, other sources of income become more important. The main source of non-wage income are transfers such as pensions and unemployment benefits.

The covariates in our estimation include gender, age and schooling of the partners in the household. Couples in which no partner or only the woman works are slightly older than in the two other household types. Women are on average a few years younger than their partners. A similar pattern emerges in the 2012/2013 wave, see table 10 in the Appendix. Schooling is highest attained schooling degree (general high school, vocational school, secondary school or no degree).

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.[15]

First, we describe the economic environment. Then we consider two equilibrium concepts: a *non-cooperative* Nash equilibrium, in which members of couples optimize considering the

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

strategy of the other party as given, and a *cooperative* equilibrium in which they solve a planner's problem that maximizes a combination of their utility. Then we show that these two equilibria have similar functional forms, and characterize the solutions for this model class.[16]

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

$$c(n_m, n_f) \leq M + w_m n_m + w_f n_f \equiv M + Y_m(w_m) + Y_f(w_f) \equiv M + Y(w_m, w_f) \tag{2}$$

where Y_i denote the wage income of each individual, and Y their joint income. When clear from the context, we omit the arguments.

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:

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

[16] A table summarizing notation is available in Appendix C.

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.

A household may or may not include children. For the sake of keeping our model consistent with the available evidence on time use, we only consider households with children who are at least seven years old. Younger children are known to impose a big tax on a couple's time and to significantly affect the partner's time allocation.[17] In this paper, we drop couples with young children from our data, and leave this topic for future research.

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

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

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.

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,

[17] In most household models, 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 (2014).

each member $i \in \{m, f\}$ of a couple solves the following decision problem:

$$\max_{n_i, h_i, l_i} U(c, z, \ell_i) \tag{5}$$

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

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

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 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, derive the optimal choices of $(\ell_i, h_i), i = m, f$, and the indirect utility functions $\hat{U}_i(n_m, n_f), i = m, f$,

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

$$n_m \mapsto n_f$$
$$n_f \mapsto n_m$$

   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

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

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

$$\begin{aligned} \frac{\ell_i}{T_i - n_i} &= \frac{1-\beta_i}{1-\beta_i+\beta_i\gamma_i} \equiv \nu_i^n \\ \frac{h_i}{T_i - n_i} &= \frac{\beta_i\gamma_i}{1-\beta_i+\beta_i\gamma_i} \equiv 1-\nu_i^n \end{aligned} \tag{6}$$

where the superscript n is for the *non-cooperative* solution. 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 thus the Nash equilibrium can be characterized by solving

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

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

$$n_i^* = \operatorname*{argmax}_{0 \le n_i \le T_i} (M + w_i n_i + w_k n_k)(T_i - n_i)^{\phi_i^n} \qquad \text{given } n_k = n_k^*, \text{for } i = m, f \tag{7}$$

where we have defined

$$\phi_i^n = \frac{1-\alpha_i}{\alpha_i}(1 - \beta_i + \beta_i\gamma_i) \tag{8}$$

to simplify the notation. In Appendix D we show the optimization problem in (7) has the solution

$$n_i = \frac{\left(T_i - \phi_i^n \frac{M + w_k n_k}{w_i}\right)^+}{1 + \phi_i^n} \qquad \text{for } i = m, f \tag{9}$$

It is insightful to investigate how labor supply reacts to changes in wages. For this, first consider

$$\frac{\partial n_i}{\partial w_k} = -\frac{\phi_i^n}{1+\phi_i^n}\frac{n_k}{w_i} < 0. \tag{10}$$

Hence, my labor supply unambiguously decreases if my partners wage increases and the corresponding cross-wage elasticity is negative. In reaction to a change in one's own wage, labor supply then reacts as follows:

$$\frac{\partial n_i}{\partial w_i} = -\frac{\phi_i^n}{1+\phi_i^n}\left(\frac{w_i w_k \frac{\partial n_k}{\partial w_i} - (M + w_k n_k)}{w_i^2}\right). \tag{11}$$

This expression is unambiguously positive, i.e., a person increases hours worked when his/her wage increases and the corresponding own-wage elasticity is positive. This is true when not taking into account the partners reaction (second part of the expression) and intensifies when taking into the partners reaction. Since a persons partner will work less when the own wage increases, a person will work even more taking this into account.

For aggregation below, we will consider changes in labor supply when preferences change (or are assigned differently). For this, it is useful to derive

$$\begin{aligned}
\frac{\partial n_i}{\partial \alpha_i} &= -\tfrac{M+n_k w_k}{w_i}\tfrac{1}{(1+\phi_i^n)^2}\tfrac{\partial \phi_i^n}{\partial \alpha_i} < 0 \\
\frac{\partial n_i}{\partial \beta_i} &= -\tfrac{M+n_k w_k}{w_i}\tfrac{1}{(1+\phi_i^n)^2}\tfrac{\partial \phi_i^n}{\partial \beta_i} > 0
\end{aligned}$$

4.3 Social planner

Now assume that the couples' problem is solved by a social planner, who weighs utilities with the Cobb-Douglas aggregator

$$u_m^{\omega_m} u_f^{\omega_f}$$

where u_m and u_f are utilities for the male and female, and are given by the function (4) as before. We normalize

$$\omega_m + \omega_f = 1$$

but keep both to simplify the notation.

We also assume that income is transferable, and that working n_m and n_f hours (given wages) will lead to a joint income as defined in (2). Thus, the planner effectively solves

$$\max_{\{c_i,n_i,\ell_i,h_i\}_{i=m,f}} \prod_{i=m,f} \left(c_i^{\alpha_i} (z^{\beta_i} \ell_i^{1-\beta_i})^{1-\alpha_i} \right)^{\omega_i} \tag{15}$$

where

$$\begin{aligned} c_m + c_f &= Y(n_m, n_f) \\ z(h_m, h_f) &= h_m^{\gamma_m} h_f^{\gamma_f} \\ n_i + \ell_i + h_i &= T_i \qquad \text{for } i = m, f \end{aligned}$$

Again, we separate the problem into two stages:

1. Given n_m, n_f,
   (a) find the optimal allocation c_m, c_f for consumption,
   (b) find the optimal allocation ℓ_i, h_i for $i = m, f$ for leisure and home production hours,
2. Using the indirect utility solution above, find the optimal n_m, n_f.

The first stage is simplified by the Cobb-Douglas structure. First, fix n_m, n_f and thus Y. Then the optimal consumption levels are

$$\frac{c_i}{Y} = \frac{\alpha_i \omega_i}{\alpha_f \omega_f + \alpha_m \omega_m} \qquad \text{for } i = m, f$$

so given the constants,

$$c_m^{\alpha_m \omega_m} c_f^{\alpha_f \omega_f} \propto Y^{\alpha_m \omega_m + \alpha_f \omega_f}$$

In a similar manner to the non-cooperative solution in Section 4.2, given fixed $\ell_i + h_i = T_i - n_i$, we solve

$$\max_{h_m,\ell_m,h_f,\ell_f} \left(h_m^{\gamma_m \beta_m} h_f^{\gamma_f \beta_m} \ell_m^{1-\beta_m} \right)^{(1-\alpha_m)\omega_m} \left(h_m^{\gamma_m \beta_f} h_f^{\gamma_f \beta_f} \ell_f^{1-\beta_f} \right)^{(1-\alpha_f)\omega_f}$$

Then

$$\frac{\ell_i}{T_i - n_i} = \frac{(1-\beta_i)(1-\alpha_i)\omega_i}{(1-\beta_i+\gamma_i\beta_i)(1-\alpha_i)\omega_i + \gamma_i\beta_k(1-\alpha_k)\omega_k} \equiv \nu_i^c$$
$$\frac{h_i}{T_i - n_i} = 1 - \nu_i^c$$

where the superscript c denotes the *cooperative* solution. Then we can write the objective (15) as

$$\max_{n_f, n_m} Y(n_m, n_f)(T_m - n_m)^{\phi_m}(T_f - n_f)^{\phi_f}$$
$$\text{st} \quad 0 \le n_f \le T_f, 0 \le n_m \le T_m, \quad \text{with}$$
$$\phi_i^c = \frac{[1-\beta_i+\gamma_i\beta_i](1-\alpha_i)\omega_i + \gamma_i\beta_k(1-\alpha_k)\omega_k}{\alpha_f\omega_f + \alpha_m\omega_m} \qquad \text{for } i = m, f$$

Again, using results from Appendix D, we can characterize the solution of this problem as

$$n_i = \frac{\left(T_i - \phi_i^c \frac{M + w_k n_k}{w_i}\right)^+}{1 + \phi_i^c} \qquad \text{for } i = m, f \tag{16}$$

Notice that *mutatis mutandis*, (9) and (16) are essentially the same function, just with different values of ϕ_i. This simplifies the analysis that follows considerably.

4.4 Equilibrium regions

We now consider solutions to problems that are characterized by the system

$$n_i = \frac{\left(T_i - \phi_i \frac{M + w_k n_k}{w_i}\right)^+}{1 + \phi_i} \qquad \text{for } i = m, f \tag{17}$$

where $\phi_i = \phi_i^n$ for the non-cooperative and $\phi_i = \phi_i^c$ the cooperative solution, 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 (17).

For analytical convenience, we introduce

$$Y_i = n_i w_i \qquad \text{for } i = m, f \tag{18}$$

for the *earnings* of the individual. This allows us to rewrite (17) as

$$Y_i = \frac{\left(T_i w_i - \phi_i(M + Y_k)\right)^+}{1 + \phi_i} \qquad \text{for } i = m, f \tag{19}$$

We solve (19) for Y_i for $i = m, f$ by considering the four possible cases, providing the complete characterization in the lemma below. Having solved for Y_i, we recover n_i from (18).[18]

Lemma 1. *The system* (19) *always has a unique solution* Y_i, Y_k, *which depends on* $M, T_i w_i, T_k w_k$ *as follows.*

1. *When*

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

the solution is

$$Y_i = 0, \qquad \textit{for } i = m, f.$$

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

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

the solution is

$$Y_i = \frac{T_i w_i - \phi_i M}{1 + \phi_i}, \quad Y_k = 0$$

3. *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

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

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

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

Proof. Guess and verify. □

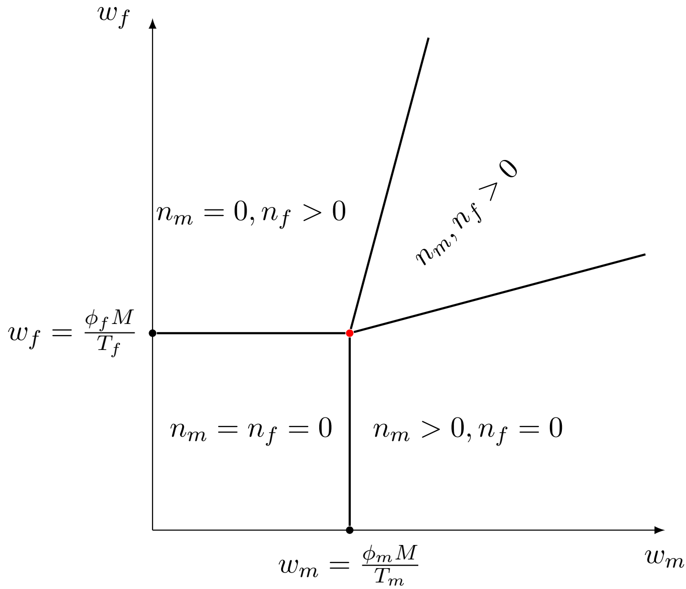

Figure 1: The four regions for work choices (see Lemma 1 and the discussion below it).

Using Lemma 1 with (18), it is easy to characterize the solution in work hours n_i; Figure 1 shows the four regions of the lemma. When

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

neither member of the couple works, since their wage are too low compared to their other income. In this case, the above is their reservation wage.

However, when person k in the couple works, this raises the reservation wage for i according to

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

Intuitively, since the couple's income from market work is shared, the income from the spouse is treated as an addition to other non-wage income.

5 Estimation

5.1 Parametric forms

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:

$$(M, w_m, w_f, \alpha_m, \alpha_f, \beta_m, \beta_f, \gamma) \mapsto (n_m, n_f, \ell_m, \ell_f, h_m, h_f) \tag{20}$$

There are two additional ingredients that are necessary to complete the specification of the data generating process of the model: a mapping from "ideal" hours in (20) to the hours observed in the data that are necessarily noisy by construction, and the specification of a cross-sectional model for the distribution of parameters. We consider each of these in turn.

As discussed in Section 3, time use information is collected in 10-minute blocks. As is common when mapping continuous data on a simplex to discrete data, we use a multinomial distribution $\text{Multinomial}(n, p_1, \dots)$, where n is an integer for the number of trials, and $p_1, \dots$ are the probabilities with $\sum_j p_j = 1$.

Let Δ denote the length of each block. We assume that the *observed* number of blocks $\hat{n}_{i,k}$, $\hat{\ell}_{i,k}$, $\hat{h}_{i,k}$ for individual i on some day k follows

$$(\hat{n}_{i,k}, \hat{\ell}_{i,k}, \hat{h}_{i,k}) \sim \text{Multinomial}(T_i/\Delta, n_i/T_i, \ell_i/T_i, h_i/T_i) \qquad \text{IID in } k\text{, conditional on } i \tag{21}$$

This ensures that the expected values are

$$\mathbb{E}\Big[(\hat{n}_{i,k}, \hat{\ell}_{i,k}, \hat{h}_{i,k})\Big] = (n_i, \ell_i, h_i)$$

We also need to assume a parametric 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 (eg between α_i, β_i, and w_i), or between spouses. In order to strike a reasonable balance between these two requirements, we use distributions of the form

$$\begin{bmatrix} \operatorname{logit}^{-1}(\alpha_m) \\ \operatorname{logit}^{-1}(\beta_m) \\ \log(w_m) \\ \operatorname{logit}^{-1}(\alpha_f) \\ \operatorname{logit}^{-1}(\beta_f) \\ \log(w_f) \end{bmatrix} \sim \operatorname{Normal}(BX, \Sigma), \qquad \text{IID} \tag{22}$$

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 (eg between α_i and w_i), but no correlation between spouses. Deviations from this would allow us to check assortative matching between couples.

It is important to emphasize that (22) 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. Below, we are careful about distinguishing *ex ante* wages, which are realizations from the distribution (22) and may or may not be observable, and *observed* wages, which are wages for the employed individuals.

5.2 Bayesian methodology

We use Bayesian indirect inference to estimate the model. Similarly to classical indirect inference algorithms,[19] we fix a set of model parameters, simulate the model equilibrium, then fit an auxiliary model that is easy to estimate but captures the key moments of the data which allow identification.

[19]See Smith (2008) for an overview.

In order to construct a posterior, we use the setup of Gallant and McCulloch (2009), which we briefly summarize here.[20] Consider a set of parameters θ, and simulate data $x(\theta)$ given these parameters.[21] Then given an auxiliary model with conditional density $p_A(x(\theta) \mid \phi)$, obtain the maximum likelihood estimate $\phi^*(x(\theta))$ for the simulated data. Finally, obtain the simulated likelihood $p_A(y \mid \phi^*(x(\theta)))$, where y is the observed data. Given a prior $p(\theta)$, our simulated posterior is

$$p(\theta \mid y) \propto p_A\big(y \mid \phi^*(x(\theta))\big)p(\theta) \tag{23}$$

Gallant and McCulloch (2009) show that intuitively, one can think of this framework as using the Kullback-Leibler divergence as a distance metric under the auxiliary model between the parameters and the observed data. A practical advantage is not having to choose or estimate a weighting matrix.

Bayesian indirect inference methods usually sample from the simulated posterior using a variant of Metropolis-Hastings (eg Marjoram et al. 2003), which is robust, but requires careful tuning to obtain reasonable mixing, and even then does not scale well with the dimension of the problem (Gelman, Carlin, et al. 2013, Chapter 11). Hamiltonian Monte Carlo methods, introduced in the 1980s,[22] provide better mixing convergence by using gradient information for the posterior. We our own implementation of a variant of the No-U-turn sampler of Hoffman and Gelman (2014), as described in Betancourt (2017), to sample from the posterior in (23). We programmed the model in the Julia language (Bezanson et al. 2017), and obtained derivatives using the automatic differentiation library of Revels, Lubin, and Papamarkou (2016).[23]

Recall from Section 5.1 that the structural parameters of the model are determined by B and Σ in (22), which are then mapped to the parameters α and β, and the wage w for each member of the couple. We choose a flat prior for the elements of B, and model the covariance matrix Σ as marginal variances σ and correlation Ω, ie

$$\Sigma = \text{diag}(\sigma) \cdot \Omega \cdot \text{diag}(\sigma)$$

where Ω is a correlation matrix, ie it is positive definite with a unit diagonal, and the

[20]Our notation follows Drovandi, Pettitt, Lee, et al. (2015), who provide an overview of Bayesian methods for indirect inference.

[21]We suppress the random variables in the notation. We use common random variables where applicable, for consistency.

[22]See Neal et al. (2011) for an overview.

[23]See Appendix F on source code for the estimation.

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

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

with $\eta = 2$, which ensures a vague but unimodal prior. For the elements of σ, we follow Polson, Scott, et al. (2012) and use the half-Cauchy prior

$$\sigma_i \sim \text{Cauchy}(0, 2.5)$$

which is also vague but sufficient to make the posterior proper.

For an auxiliary model, we model leisure $\ell_{i,j}$, market hours $n_{i,j}$, and market income $Y_{i,j}$ for each couple j as a vector valued regression for the six values (note that $i = m, f$) on M_j and covariates for each couple. Our auxiliary parameters ϕ are the coefficient matrix and variance matrix of this regression.

The advantage of this approach is that it deals with the problem of missing wages for the non-employed in a continuous manner: for a non-employed person, $n_{i,j} = 0$ implies $Y_{i,j}$ by construction, while when $n_{i,j} > 0$ the income $Y_{i,j}$ maps to the wage $w_{i,j}$. This makes the link function $\theta \mapsto \phi$ continuous.

Since the dimension ϕ is larger than θ , our model is technically *overidentified.* We check local identification by calculating singular values of the Jacobian of the link function $\theta \mapsto \phi$ using simulated data, and find that identification is robust.[24] Convergence statistics of MCMC are available in Appendix E.

5.3 Exploring identification: singles

In this section we develop intuition for the identification of the model using a simplified version, which uses the same building blocks to model the time use of *single* individuals. While such a model may be important in its own right, here we use it to discuss the issues that arise in the estimation of our model in a simplified setting, since we can discuss various questions that arise in both models, without the algebraic complications of the couples' decision functions. In order to keep the discussion simple, we pretend that there is no observation error, and individual time-use choices are observed perfectly.

[24] The next section provides further intuition on identification using a simplified setting.

Consider the individual analogue of (5),

$$\max_{n_i,h_i,\ell_i} (M_i + n_i w_i)^{\alpha_i} \left(z_i^{\beta_i} \ell_i^{1-\beta_i} \right)^{1-\alpha_i} \qquad \text{st} \qquad z_i = h_i^{\gamma}, \quad n_i + h_i + \ell_i \leq T \tag{24}$$

where the individual chooses market, home production, and leisure hours to maximize utility, which depends on consumption, home production, and leisure. In contrast to our model of couples, here there is no strategic interaction, so the problem is considerably simpler.

Fixing n_i, we solve

$$\max_{h_i,\ell_i} h_i^{\gamma\beta_i} \ell^{1-\beta_i} \qquad \text{st} \qquad h_i + \ell_i \leq T - n_i$$

as

$$h = \frac{\gamma\beta}{\gamma\beta + 1 - \beta}(T - n) \qquad \ell = \frac{1 - \beta}{\gamma\beta + 1 - \beta}(T - n) \tag{25}$$

Then (24) can be written as

$$\max(M + nw)(T - n)^{\phi} \qquad \text{where} \qquad \phi = \frac{1 - \alpha}{\alpha}(\gamma\beta + 1 - \beta) \tag{26}$$

Notice the similarity to (8). Using results from (30), we obtain

$$Y = nw = \frac{(Tw - \phi M)^+}{1 + \phi} \tag{27}$$

Note that we observe M_i, ℓ_i, h_i, and n_i for *all* individuals, and in addition, we observe w_i whenever $n_i > 0$.

We can now state the following results concerning identification:

1. γ and β_i cannot be identified separately for singles: only the ratio

$$\frac{h_i}{\ell_i} = \frac{\gamma\beta_i}{1 - \beta_i}$$

   is identified. This can be seen from (25) and (26), since all terms that have β_i and γ are transformations of h_i/ℓ_i.

2. Fixing γ (eg at $\gamma = 1$ for algebraic simplicity), we can always identify β_i from h_i/ℓ_i for all individuals, regardless of their employment status.

3. From (27), we always identify ϕ_i, and thus consequently α_i (conditional on identifying

β_i and γ as discussed above) whenever $n_i > 0$, ie the individual is *employed*.

4. However, when the individual is *nonemployed*, we only know that

$$n_i = 0 \qquad \Leftrightarrow \qquad Tw_i < \phi_i M_i$$

which does not even allow us to restrict the individual's ϕ_i, since w_i is not known for employed either.

However, the fact that we cannot identify ϕ_i's (and thus α_i's) *individually* does not prevent us from making inferences about their *distribution*. In order to do this, assume that individual (α_i, β_i, w_i) triples are drawn from a parametric distribution

$$(\alpha_i, \beta_i, w_i) \sim F(X_i; \theta), \quad \text{IID}$$

where X_i is a vector of covariates, such as gender and age, and θ parameterizes the distribution. An example of this would be a construct very similar to (22),

$$\theta = (\mu, \Sigma)$$

$$\begin{bmatrix} \text{logit}^{-1}(\alpha_i) \\ \text{logit}^{-1}(\beta_i) \\ \log(w_i) \end{bmatrix} \sim \text{Normal}(\mu, \Sigma), \quad \text{IID}$$

which would allow a flexible correlation structure between α_i, β_i, and w_i for individuals, while at the same time imposing a low-dimensional parametric family constrained to the appropriate intervals.

This source of identification is usually called *overlap* in statistical modeling (Gelman and Hill 2007, Chapter 10), which for our model manifests in the variation of other incomes M_i and covariates X_i. In order to see this in practice, consider a hypothetical scenario where all individuals have the same $M_i = M$, and let's assume that all have the same wage w. In this case, while we would know the ϕ_i's and the α_i's for the *employed*, for the *nonemployed* all we could infer is that

$$Tw \leq \phi_i M = \frac{1-\alpha_i}{\alpha_i}(\gamma\beta + 1 - \beta) \qquad \Leftrightarrow \qquad \alpha_i \leq \frac{1}{1 + \frac{M}{Tw}(\gamma\beta + 1 - \beta)} \equiv \bar{\alpha}$$

Figure 2 illustrates that in this case, our assumptions about the parametric family would impose the distribution of α_i for the nonemployed, which could not be confirmed or refuted by the data.

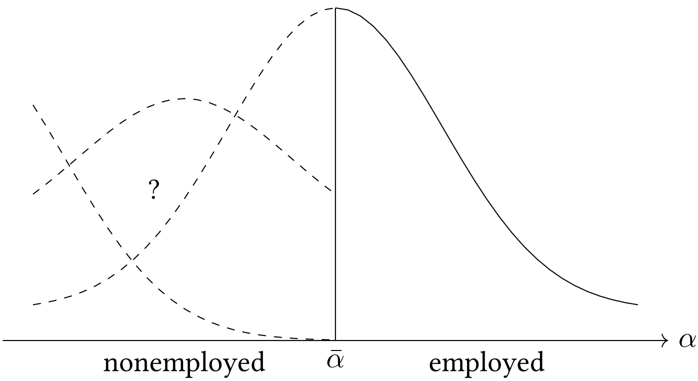

Figure 2: Illustration of no overlap. Fixing wage, and imposing a constant M, all we would identify is the distribution of the α's of the employed (solid line), while for the nonemployed, all we would know that their α is below some cutoff, and the distribution would be imposed by our assumptions on the parametric family (dashed lines).

Now consider the case when there is variation in M_i. In this case, individuals would make different labor choices not just because of their different preferences α_i, but also because they have varying levels of other income. Consequently, the α_i's for the employed and non-employed individuals would *overlap*, allowing us to identify the distribution. Similarly, if we model wages as a Mincer regression using covariates X_i, the more overlap we have between employed and non-employed individuals, the better the distribution of α_i's is identified for the non-employed. Consequently, it is important to check the overlap for the data.

6 Results

6.1 Posterior checks

In this section we analyze the predictions of the model and compare it to the data. The result of Bayesian estimation is a posterior *distribution* for the model parameters θ, which allows us to consider uncertainty. Since the parameters that characterize the cross-sectional distribution are difficult to map to observables intuitively because of the various transformations in Section 5.1, we mostly discuss the implied observables.

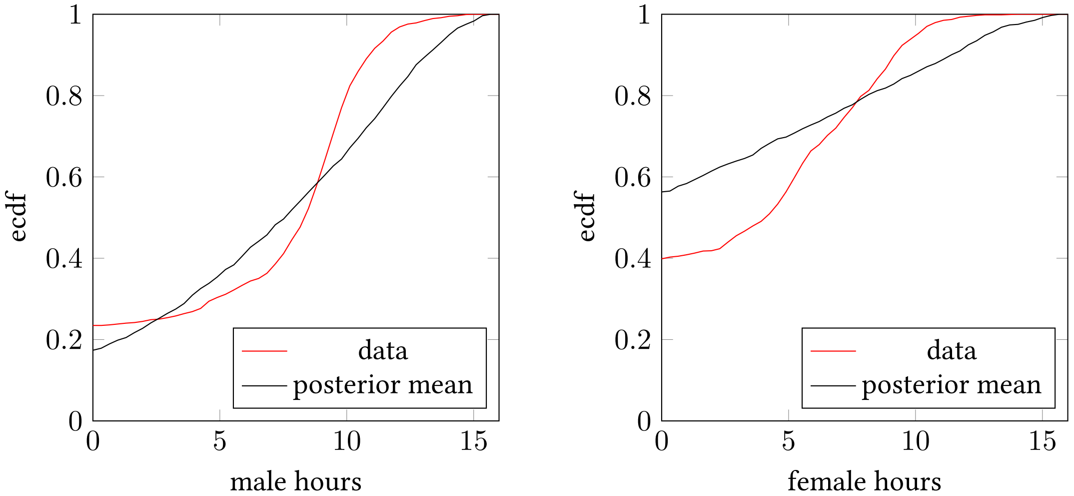

Figure 3: Observed and predicted working hours (relative to total time endowment) by gender, in the data (red) and the model (red, at the posterior mean); left: male, right: female.

Figure 3 shows the empirical CDFs for hours for the data and the posterior mean parameters, while Figure 4 shows the same data using histograms. Observe that while the employment of males is predicted reasonably well (about 20% are non-employed, both in the model and the data), female non-employment is not matched well by the model: about 40% of women in the data work 0 hours, as opposed to 55% predicted. The distributions in the data also show much more concentration than in the model: the hours of males are concentrated around 8–9 hours/day ($\approx$ 55% of the total time endowment of 16 hours) in data, the simulated predictions match the mean (by construction) but not the dispersion. This is not surprising, as there is no mechanism in the model that favors the traditional full-time working hours.

Figure 5 compares the distribution of wages in the data and wages simulated from the estimated model at the posterior mean of the estimated parameters. The wages displayed are *observed wages*, different from the *ex ante* wage offer distribution on which the agents in our simulations base their employment decision. These observed wages are then wages that are actually paid out to persons choosing to supply a positive amount of hours in the market, otherwise their wages are unobserved. One can see that our simulations match the empirical wage distribution fairly well.

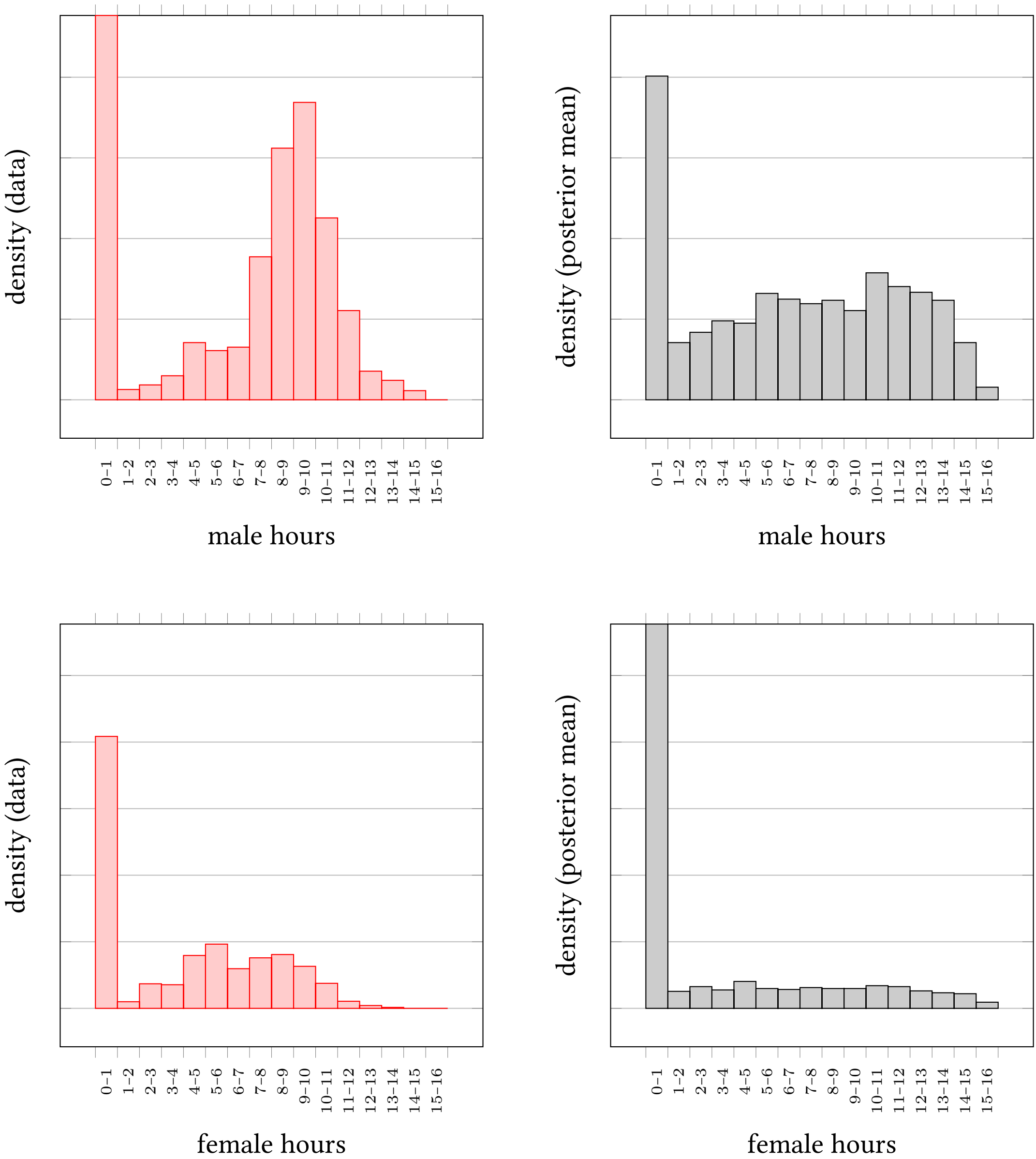

Figure 4: Histogram of observed and predicted hours, in the data (left) and at the posterior mean (right). Top: male, bottom: female.

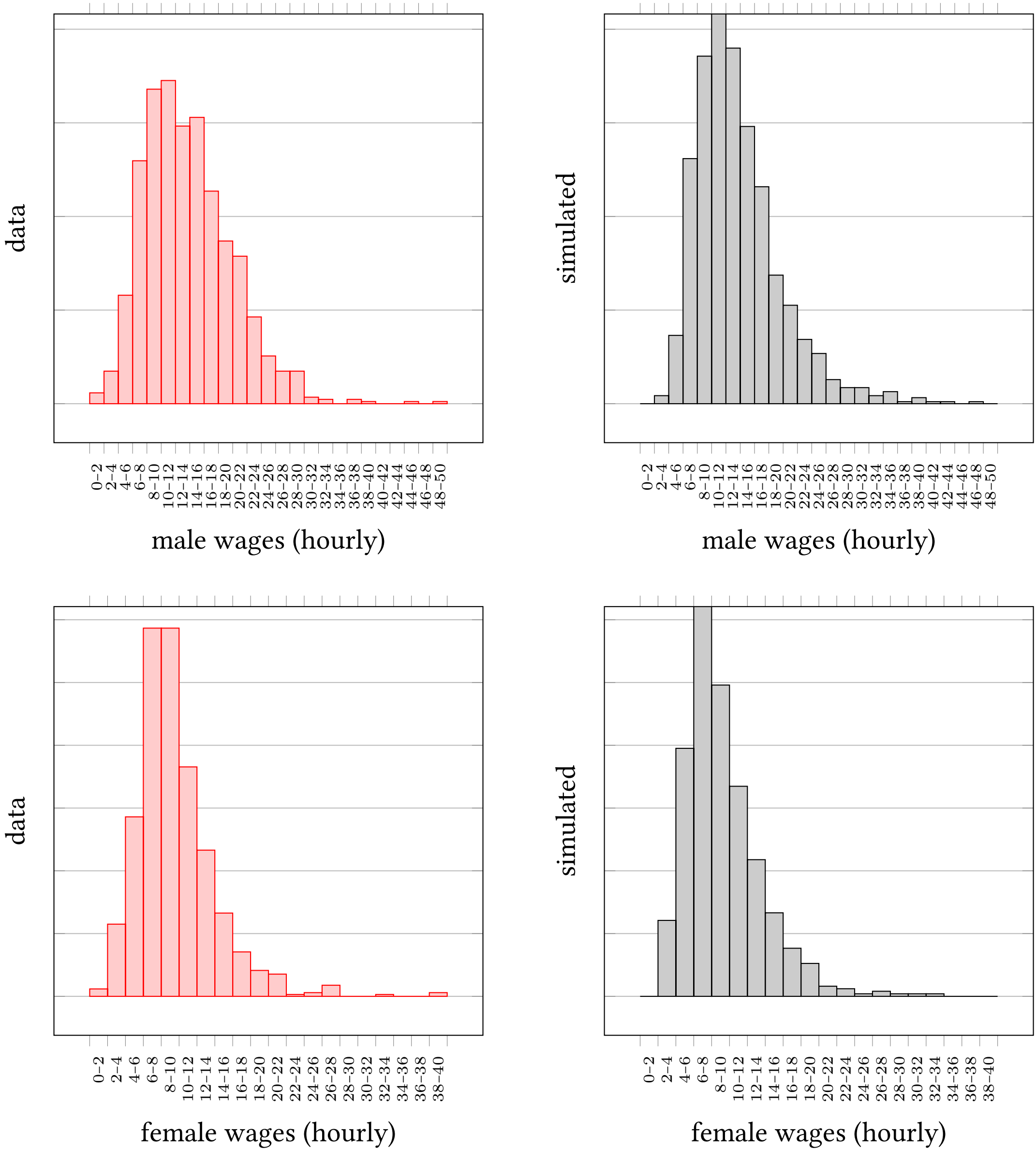

Figure 5: Wages by gender. Left: data, right: simulation at posterior mean. Top: male, bottom: female.

6.2 Counterfactuals

We now use the estimated model as a laboratory to perform counterfactual experiments. First, we consider increasing the *ex ante* wages for just males, then just females, and then for both partners by 10%.

In order to analyze the results, we calculate summary statistics by gender, such as the employment rate and average hours n, the latter also conditional on employment, wages, and leisure hours. We also split the sample into households where both members of the couple are employed (EE), only the male or the female is employed (EN) and (NE), and both are non-employed (NN). For these subsamples, we calculate their population share, market- and leisure hours, and wages (conditional on employment).

Each of these variables is a distribution for each gender (and subset of the population). We summarize this distribution by its mean, standard deviation, and 20%, 40%, 60%, and 80% quantiles. Finally, when we display the results, we show a *percentage change* of the relevant statistic, compared to the same statistic simulated from the model without any modification. In this case, the percentage changes divided by 10 show the wage elasticity of the given statistic.[25]

Tables 2 and 20 show the effect of increasing *ex ante* wages for males and females, but not their partners, respectively. Ex ante wage increases by 10% translate into about 9.7% overall wage changes *ex post*. Male hours increase by about 2.6%, while female hours decrease by about 4.4% when males experience an *ex ante* wage increase by 10%. The reverse happens following an increase in female wages, but females increase hours by more and males decrease hours by less compared to when male wages change. Hence, albeit being small in general, own-wage and cross-wage elasticities are larger for females than for males. Note that these changes in hours are the result of changes both along the intensive and along the extensive margin of employment. Changes in the intensive margin are primarily determined by the households in which one or both partners are employed. Changes in the extensive margin describe changes between the different types of household according to which one partner or both partners change his/her/their employment status. It is then easy to see that most of the changes in hours are driven by changes in the extensive rather than the intensive margin of employment, since the overall change in hours is basically identical

[25] Also, in order to reduce noise, we use common random variables in the calculations. Each relative change is the average of simulations from the posterior, though in practice the results would not change appreciably if we used the posterior mean.

to the change in the employment rate and the change in hours for those that are employed is fairly small.

Equation (10) has shown that cross-wage elasticities are negative along the intensive margin. In case of an increase in male wages, females therefore both decrease their hours and drop out of employment as can be seen from the changes in shares of households with both partners or only the females employed. The fact that average hours in these two types of households increase points to the fact that those females that drop out were many and were working relatively few hours. Different to the overall effects, cross-wage elasticities for females within the aforementioned households are therefore positive due to changes in composition. Equation (11) has shown positive own-wage elasticities. Again, persons enter employment at very low hours and therefore cause compositional changes which result in negative own-wage elasticities for some households types (see e.g. female hours in households in which both partners work).

Table 4 shows the effect of increasing *ex ante* wages for both partners. Both female and male employment increases by approximately 1%, with a very small effect on average work hours *per se* (conditional on employment). This can be understood from aggregating the previous effects of increasing wages separately for males and females which cancel each other out, at least to some extent, when wages are increased for both partners. In particular, movements along the extensive margin still drive most of the dynamics in hours, but are reduced to a large extent.

6.3 Aggregation

We quantify the influence of preferences and wages by replacing them with their *cross-sectional averages* for males, females, or both, then calculating hours using the model setup in Section 4. For preferences, this means replacing a couple with a synthetic one that has preferences

$$\bar{\alpha}_i = E[\alpha_i], \quad \bar{\beta}_i = E[\beta_i], \quad \text{for } i = m, f$$

from the distribution defined in (22), but keeping the wages from the same distribution.

Figure 6 shows the distributions of α and β as well as *ex ante* wages simulated at the posterior mean parameters for males and females respectively. Vertical lines indicate the respective mean values that we aggregate up to. Considering α, one can see that men weigh consumption higher than home production as leisure than women on average. In addition

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.8	7.1	9.0	7.0	30	14.0	7.3	9.0	6.9	2	14.8	8.7	0	—	—	0
EN	50	14.4	9.1	—	0.0	0	—	—	—	—	50	15.8	9.2	0	—	—	0
NE	13	—	0.0	10.1	9.1	1	12.8	0.4	9.6	8.7	0	—	—	12	10.1	9.1	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	0	—	—	0	—	—	4

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	2.6	-1.1	—	—	—	—	-4.4	-1.2	—	—	—	—
Δe	all	2.1	—	—	—	—	—	-4.2	—	—	—	—	—
Δn	all/E	0.5	-0.3	1.4	0.7	0.4	0.2	-0.1	-0.0	-0.3	-0.2	-0.1	-0.1
Δw	all/E	9.7	9.8	9.6	9.6	9.7	9.7	0.3	0.3	0.3	0.3	0.3	0.3
$\Delta \ell$	all	-1.9	-1.2	-2.0	-2.2	-2.5	-2.2	1.2	-0.5	3.2	2.0	1.1	0.5
Δp	EE	-1.8	—	—	—	—	—	-1.8	—	—	—	—	—
Δn	EE	-0.1	-0.0	0.1	-0.1	-0.2	-0.0	0.3	-0.1	1.1	0.6	0.3	0.1
Δw	EE	9.3	9.2	9.3	9.2	9.2	9.3	0.5	0.5	0.5	0.5	0.6	0.5
$\Delta \ell$	EE	0.2	0.1	0.3	0.3	0.2	0.2	-0.3	-0.2	-0.5	-0.4	-0.4	-0.2
Δp	EN	4.7	—	—	—	—	—	4.7	—	—	—	—	—
Δn	EN	0.2	-0.3	0.5	0.2	0.1	0.0	—	—	—	—	—	—
Δw	EN	9.6	9.7	9.5	9.6	9.6	9.6	—	—	—	—	—	—
$\Delta \ell$	EN	-0.2	-0.2	-0.1	-0.1	-0.1	-0.2	-0.1	0.0	-0.1	-0.1	-0.1	-0.0
Δp	NE	-10.0	—	—	—	—	—	-10.0	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	0.5	-0.1	1.3	0.8	0.5	0.2
Δw	NE	—	—	—	—	—	—	0.5	0.6	0.4	0.4	0.5	0.5
$\Delta \ell$	NE	0.1	-0.3	0.2	0.1	0.0	0.0	-0.7	-0.2	-1.0	-1.0	-0.8	-0.6
Δp	NN	-8.7	—	—	—	—	—	-8.7	—	—	—	—	—
$\Delta \ell$	NN	0.1	-0.4	0.3	0.1	0.0	-0.0	-0.0	-0.0	0.1	-0.0	-0.0	-0.0

Table 2: Increasing wages by 10%, for *males only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	31	12.8	7.0	9.9	7.4	0	—	—	1	10.7	9.0	0
EN	50	14.4	9.1	—	0.0	2	13.3	8.4	9.4	0.5	48	14.4	9.1	0	—	—	0
NE	13	—	0.0	10.1	9.1	0	—	—	—	—	0	—	—	13	11.1	9.2	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	0	—	—	0	—	—	5

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	-1.6	0.7	—	—	—	—	5.5	1.3	—	—	—	—
Δe	all	-1.4	—	—	—	—	—	5.3	—	—	—	—	—
Δn	all/E	-0.2	0.2	-0.6	-0.3	-0.1	-0.1	0.3	0.0	0.7	0.5	0.3	0.2
Δw	all/E	0.2	0.2	0.3	0.3	0.2	0.2	9.6	9.7	9.5	9.6	9.6	9.6
$\Delta \ell$	all	1.2	0.7	1.2	1.4	1.6	1.4	-1.5	0.5	-3.8	-2.5	-1.4	-0.7
Δp	EE	3.2	—	—	—	—	—	3.2	—	—	—	—	—
Δn	EE	0.1	0.0	0.4	0.2	0.1	0.1	-0.3	0.1	-0.5	-0.6	-0.4	-0.2
Δw	EE	0.6	0.6	0.5	0.6	0.6	0.6	9.4	9.5	9.3	9.4	9.3	9.3
$\Delta \ell$	EE	-0.2	-0.1	-0.2	-0.2	-0.3	-0.2	0.3	0.2	0.6	0.5	0.4	0.3
Δp	EN	-4.4	—	—	—	—	—	-4.4	—	—	—	—	—
Δn	EN	0.3	-0.1	0.6	0.4	0.3	0.1	—	—	—	—	—	—
Δw	EN	0.3	0.3	0.3	0.4	0.3	0.4	—	—	—	—	—	—
$\Delta \ell$	EN	-0.4	-0.2	-0.5	-0.5	-0.5	-0.4	0.1	-0.0	0.1	0.1	0.1	0.0
Δp	NE	10.5	—	—	—	—	—	10.5	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	0.2	-0.3	0.7	0.1	0.0	0.0
Δw	NE	—	—	—	—	—	—	9.5	9.5	9.5	9.5	9.5	9.6
$\Delta \ell$	NE	-0.1	0.2	-0.2	-0.1	-0.0	-0.0	-0.1	-0.2	0.2	-0.1	0.1	-0.1
Δp	NN	-4.1	—	—	—	—	—	-4.1	—	—	—	—	—
$\Delta \ell$	NN	-0.0	0.0	0.0	-0.1	-0.0	-0.0	0.1	0.0	0.2	0.1	0.1	0.1

Table 3: Increasing wages by 10%, for *females only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	32	14.0	7.1	9.9	7.0	0	—	—	0	—	—	0
EN	50	14.4	9.1	—	0.0	0	—	—	—	—	50	15.8	9.2	0	—	—	0
NE	13	—	0.0	10.1	9.1	0	—	—	—	—	0	—	—	13	11.1	9.3	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	0	—	—	0	—	—	4

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	1.1	-0.4	—	—	—	—	1.1	0.3	—	—	—	—
Δe	all	0.8	—	—	—	—	—	1.0	—	—	—	—	—
Δn	all/E	0.3	-0.1	0.7	0.4	0.2	0.1	0.1	0.0	0.3	0.2	0.1	0.1
Δw	all/E	9.9	9.9	9.9	9.9	9.9	9.9	9.9	9.9	10.0	9.9	9.9	9.9
$\Delta \ell$	all	-0.8	-0.4	-0.9	-1.0	-1.0	-0.9	-0.3	0.1	-0.9	-0.5	-0.3	-0.1
Δp	EE	1.6	—	—	—	—	—	1.6	—	—	—	—	—
Δn	EE	0.1	-0.0	0.3	0.2	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.1
Δw	EE	9.9	9.9	9.9	9.9	9.9	9.9	9.9	10.0	9.9	9.9	9.9	9.9
$\Delta \ell$	EE	-0.1	-0.0	-0.1	-0.1	-0.1	-0.1	-0.0	0.0	-0.1	-0.0	-0.0	-0.1
Δp	EN	0.3	—	—	—	—	—	0.3	—	—	—	—	—
Δn	EN	0.5	-0.5	1.2	0.6	0.3	0.2	—	—	—	—	—	—
Δw	EN	9.9	10.0	9.9	9.9	9.9	9.9	—	—	—	—	—	—
$\Delta \ell$	EN	-0.6	-0.5	-0.6	-0.7	-0.6	-0.6	0.0	-0.0	0.0	0.0	0.0	0.0
Δp	NE	-0.3	—	—	—	—	—	-0.3	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	0.6	-0.5	1.6	0.8	0.4	0.2
Δw	NE	—	—	—	—	—	—	10.1	10.0	10.1	10.1	10.1	10.0
$\Delta \ell$	NE	0.0	-0.1	0.1	0.0	0.0	0.0	-0.7	-0.4	-0.9	-0.9	-0.9	-0.7
Δp	NN	-12.2	—	—	—	—	—	-12.2	—	—	—	—	—
$\Delta \ell$	NN	0.1	-0.3	0.3	0.1	0.0	-0.0	0.0	-0.1	0.2	-0.0	-0.0	-0.0

Table 4: Increasing wages by 10%, for *both members* of the couple. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

to this difference in means, the distribution is slightly left skewed for men and strongly right skewed for women. The opposite is true for β, i.e. women weigh home production higher than men, their distribution is left skewed while the corresponding male distribution is right skewed.

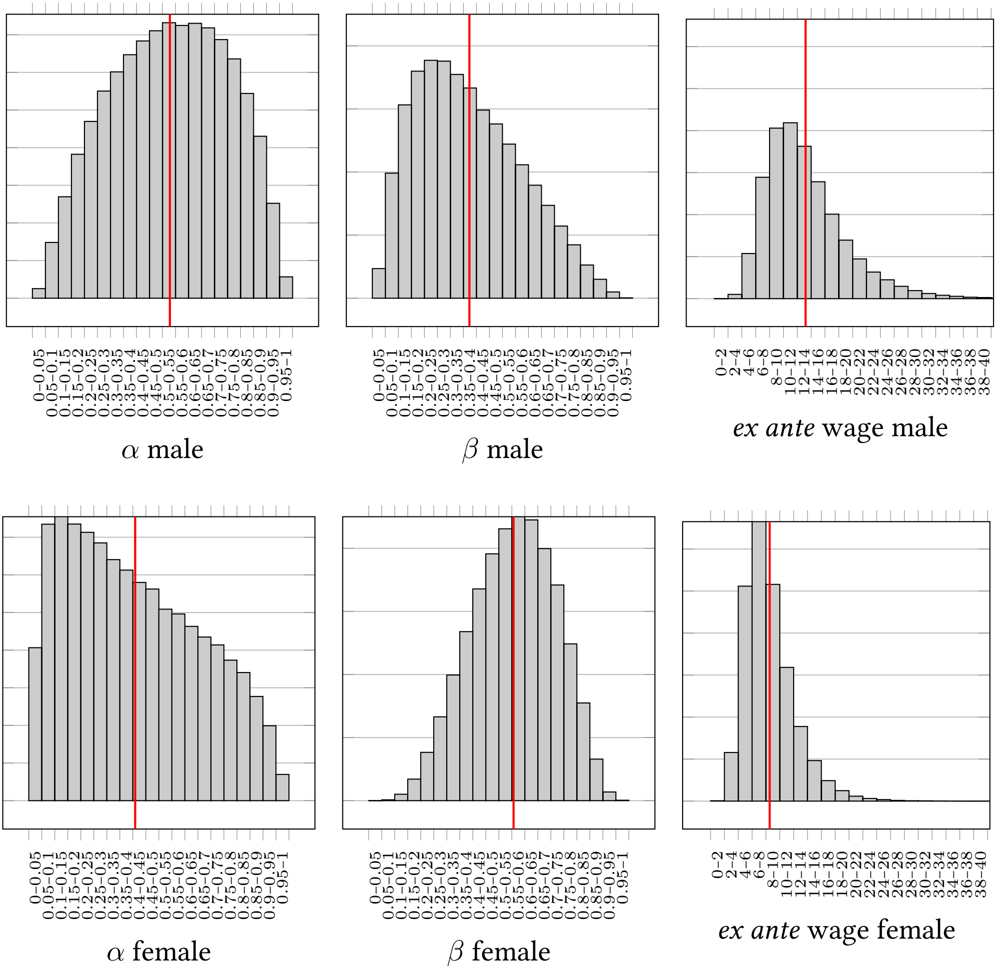

Figure 6: Aggregated preferences and *ex ante* wages. Distributions are shown of the relevant variables, which are replaced by their mean (red vertical line). Values shown are simulated at the posterior mean parameters.

Tables 5, 6, and 7 show the effect of aggregating *preferences* for both members of the couple, just males, and just females, respectively. We use the same summary statistics as in

Section 6.2.

First, and most importantly, aggregation reduces the standard deviation of market and leisure hours by roughly 50% for the affected gender(s), in the general population and among the employed. Since for the non-employed leisure ℓ depends only on β, it is not surprising that aggregating collapses its variance for these subgroups. Interestingly, aggregating the preferences also decreases the standard deviation of the wage distribution by around 1/3 in subgroups which are employed, but this does not show up in the aggregate.

Aggregation yields a negligible increase in male hours, which comes from a combination of a 16% increase in employment rate and a 13% decrease in average hours (conditional on employment). In contrast, female hours decreased by 62%, and almost all of it is an adjustment on the intensive margin.

Looking at the intensive margin, the effects is a composition of a change in α and β. From equations 12, we know that an increase in α increases hours, while an increase in β decreases hours. Which effects dominates then depends on the relative size of the change in the parameters. For men, this explains why hours change differently at the tails of the distribution (men with high α work a lot and experience a decrease in α and vice versa). In turn, a substantial number of women experiences a decline in α which is often large due to the skewness of the distribution. If these women experience a large increase in β at the same time, this might explain the substantial drop in hours at the intensive margin that we see for females. Also, as the share of couples where both partners are employed *increased* by more than 20%, composition effects similar to the ones mentioned above possibly play a role in the drop in average hours at the lower tail of the distribution for women.

Performing a similar exercise aggregating wages, the changes in levels are smaller compared to the aggregation of preferences, and mostly driven by the employment rate (see further tables in Appendix B). This is in line with the results in section 6.2. This means that preferences are extremely important to describe the distribution of labor-leisure choices, especially for females. This means that assigning the same/aggregate preferences to females biases female hours worked downwards or, put differently, from the viewpoint of average preferences and given the distribution in wages, women work too much. Also, from the viewpoint of aggregate preferences, male labor supply at the tails cannot be explained well.

	from					to EE					to EN			to NE			to NN
	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	$p_\%$	w_f	n_f	$p_\%$
EE	32	12.7	7.1	9.0	7.0	16	10.3	6.9	10.6	3.3	15	15.6	8.1	0	—	—	0
EN	50	14.4	9.1	—	0.0	15	10.6	7.1	10.2	2.8	33	16.3	7.7	0	—	—	1
NE	13	—	0.0	10.1	9.1	7	9.7	6.0	11.2	3.7	5	13.8	6.4	1	—	—	1
NN	5	—	0.0	—	0.0	0	—	—	—	—	3	13.1	3.8	0	—	—	2

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	1	-45	—	—	—	—	-62	-58	—	—	—	—
Δe	all	16	—	—	—	—	—	-9	—	—	—	—	—
Δn	all/E	-13	-44	23	-1	-14	-24	-58	-54	-62	-61	-60	-57
Δw	all/E	-2	-2	-1	-2	-2	-2	16	-1	24	19	16	12
$\Delta \ell$	all	1	-50	76	14	-11	-23	19	-66	99	43	10	-10
Δp	EE	24	—	—	—	—	—	24	—	—	—	—	—
Δn	EE	-4	-49	72	19	-6	-23	-55	-54	-54	-55	-56	-56
Δw	EE	-19	-34	-12	-15	-18	-21	18	-1	27	22	18	14
$\Delta \ell$	EE	6	-55	73	17	-6	-17	48	-60	171	82	41	13
Δp	EN	11	—	—	—	—	—	11	—	—	—	—	—
Δn	EN	-18	-39	1	-6	-15	-26	—	—	—	—	—	—
Δw	EN	10	-2	16	13	10	7	—	—	—	—	—	—
$\Delta \ell$	EN	26	-44	125	42	11	-1	2	-100	31	7	-7	-18
Δp	NE	-89	—	—	—	—	—	-89	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	-50	-36	-60	-54	-48	-45
Δw	NE	—	—	—	—	—	—	57	23	77	66	58	50
$\Delta \ell$	NE	-0	-100	18	0	-9	-15	73	-42	238	123	73	35
Δp	NN	-31	—	—	—	—	—	-31	—	—	—	—	—
$\Delta \ell$	NN	0	-100	20	1	-8	-15	2	-100	31	7	-6	-17

Table 5: Aggregating *preferences*, for *both members* of the couple. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

from					to EE					to EN			to NE			to NN
	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	$p_\%$	w_f	n_f	$p_\%$
EE	32	12.7	7.1	9.0	7.0	27	12.9	6.0	8.9	7.7	3	14.3	8.7	2	12.0	10.3	0
EN	50	14.4	9.1	—	0.0	3	13.1	7.5	8.7	1.5	46	14.6	7.9	0	—	—	1
NE	13	—	0.0	10.1	9.1	9	11.4	4.7	9.7	8.1	2	12.8	7.7	3	12.1	9.9	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	3	12.4	3.9	0	—	—	2

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	-5	-39	—	—	—	—	-5	-1	—	—	—	—
Δe	all	13	—	—	—	—	—	-4	—	—	—	—	—
Δn	all/E	-16	-39	9	-6	-15	-24	-0	1	-3	-1	-0	0
Δw	all/E	-1	-2	0	-1	-1	-1	1	0	1	1	1	1
$\Delta \ell$	all	6	-45	74	17	-6	-16	1	-0	3	2	1	1
Δp	EE	21	—	—	—	—	—	21	—	—	—	—	—
Δn	EE	-18	-43	25	-2	-17	-28	4	1	10	7	5	3
Δw	EE	-2	-4	-0	-1	-2	-2	1	-2	2	2	1	1
$\Delta \ell$	EE	17	-50	86	30	6	-6	-3	-1	-7	-5	-4	-3
Δp	EN	9	—	—	—	—	—	9	—	—	—	—	—
Δn	EN	-15	-42	11	-2	-14	-26	—	—	—	—	—	—
Δw	EN	0	-1	1	0	0	-0	—	—	—	—	—	—
$\Delta \ell$	EN	23	-47	125	38	7	-6	0	-0	0	0	0	0
Δp	NE	-66	—	—	—	—	—	-66	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	9	-1	22	16	10	4
Δw	NE	—	—	—	—	—	—	19	17	19	19	20	20
$\Delta \ell$	NE	-0	-100	18	0	-9	-15	-13	-4	-18	-18	-17	-13
Δp	NN	-45	—	—	—	—	—	-45	—	—	—	—	—
$\Delta \ell$	NN	0	-100	19	1	-9	-15	-0	0	0	-0	-0	-0

Table 6: Aggregating *preferences*, for *males only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

from						to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	16	11.0	7.1	10.2	3.3	15	14.8	9.8	1	10.9	7.2	0
EN	50	14.4	9.1	—	0.0	13	11.4	6.9	9.8	2.9	35	15.7	9.8	2	10.2	6.4	0
NE	13	—	0.0	10.1	9.1	3	11.6	1.9	9.8	5.2	1	—	—	8	10.8	6.1	2
NN	5	—	0.0	—	0.0	0	—	—	—	—	0	—	—	1	10.2	2.5	4

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	3	1	—	—	—	—	-47	-46	—	—	—	—
Δe	all	0	—	—	—	—	—	-1	—	—	—	—	—
Δn	all/E	2	0	4	4	3	1	-47	-43	-51	-50	-47	-44
Δw	all/E	0	-0	0	0	0	0	10	2	13	11	10	8
$\Delta \ell$	all	-2	1	-4	-4	-3	-1	15	-56	79	38	10	-10
Δp	EE	1	—	—	—	—	—	1	—	—	—	—	—
Δn	EE	-8	-4	-8	-10	-10	-7	-52	-51	-52	-53	-53	-52
Δw	EE	-12	-18	-9	-10	-12	-13	12	3	15	14	12	10
$\Delta \ell$	EE	7	-2	17	12	7	3	46	-57	162	78	39	13
Δp	EN	-0	—	—	—	—	—	-0	—	—	—	—	—
Δn	EN	7	-5	19	11	6	3	—	—	—	—	—	—
Δw	EN	7	0	11	9	7	6	—	—	—	—	—	—
$\Delta \ell$	EN	-10	-6	-11	-12	-12	-11	2	-100	31	7	-7	-18
Δp	NE	-5	—	—	—	—	—	-5	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	-36	-42	-30	-28	-31	-39
Δw	NE	—	—	—	—	—	—	5	2	7	6	6	5
$\Delta \ell$	NE	0	-1	1	1	0	0	53	-48	210	85	42	19
Δp	NN	7	—	—	—	—	—	7	—	—	—	—	—
$\Delta \ell$	NN	-0	1	-0	-0	-0	-0	2	-100	31	7	-7	-17

Table 7: Aggregating *preferences*, for *females only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

6.4 Predictions

Our data is not guaranteed to be representative, but that does not preclude us from using our model to make predictions that are correct for the general population, provided we make the appropriate corrections using the sample weights which are available in the dataset.

Consider a statistic $q(M_j, w_{m,j}, w_{f,j}, \alpha_{m,j}, \alpha_{f,j}, \beta_{m,j}, \beta_{f,j}, \gamma; \chi)$ for couple $j \in \mathcal{C}$. This could be, for example, the Frisch elasticity of labor supply, the response of employment to some policy experiment parameterized by χ, or some statistic that we can compare to existing aggregates that is useful for model checking, such as hours or wages. This statistic can be model-based, and all we assume is that it can be calculated from the above parameters.[26]

We are interested in aggregates of q, ie

$$Q(\chi) = \int q(M, w_m, w_f, \alpha_m, \alpha_f, \beta_m, \beta_f, \gamma)\, dF(M, w_m, w_f, \alpha_m, \alpha_f, \beta_m, \beta_f)$$

where F is a hypothetical cross-sectional distribution that describes the whole universe of couples. Of course, F is not known, as the parameters α and β are not observed, moreover, our model is an abstraction that is very unlikely to capture the full richness of data along other dimensions, and thus F as written above may be conceptually misleading.

However, we can approximate $Q(\chi)$ above by using sample weights. Let ζ_j denote sample weights for a couple jointly.[27] We present various alternative ways of approximating $Q(\chi)$, depending on

1. whether we use (22) to model the wages, or use wage data directly when available,
2. whether we use individuals in the sample to make predictions, or we are interested in predictions for individuals who were not in the sample (the superpopulation).

We index posterior draws by $l \in \mathcal{L}$. Define

$$Q^{1,S,p}(\chi, l) = \sum_{j \in \mathcal{C}} \zeta_j q(M_j, w_{m,j,l}, w_{f,j,l}, \alpha_{m,j,l}, \alpha_{f,j,l}, \beta_{m,j,l}, \beta_{f,j,l}, \gamma_l) \qquad \text{for } p = c, u \tag{28}$$

[26]For statistics which also involve single individuals outside couples, we define

$$q(M_j, w_{s,j}, \alpha_{s,j}, \beta_{s,j}, \gamma; \chi)$$

for individuals $j \in \mathcal{I}$, and while the notation below is for statistics that are based on couples only, it can be extended trivially to the whole population.

[27]We can extend this notation to singles too, with some sample weight ζ_j for $j \in \mathcal{I}$, then sums are over $\mathcal{I} \cup \mathcal{C}$.

where the subscript stands for *conditional* and *unconditional* versions, and $w_{i,j,l}$, $\alpha_{i,j,l}$, $\beta_{i,j,l}$ are drawn stochastically as defined below. The superscript S refers to the *sample*, and 1 to the fact that we use one replication for each couple.

For the conditional version of Q,

1. If $n_{m,j} = n_{f,j} = 0$, ie both members are non-employed, $w_{i,j,l}$ for $i = m, f$ are drawn from (22), conditional on $n_{m,j} = n_{f,j} = 0$, using the characterization of Lemma 1.

2. If $n_{i,j} > 0$ but $n_{k,j} = 0$ for $i = m, f$, $w_{i,j,k}$ is drawn from (22), again conditional on employment status, while $w_{i,j,l} = w_{i,j}$.

3. Finally, if both members are employed, $w_{i,j,l} = w_{i,j}$ for $i = m, f$.

The construction of $Q^{1,S,c}$ ensures that wages match the data when available, and provide wages consistent with the data and the model (in a probabilistic sense) when they are not. For all possible cases, it is ensured that

$$n_{i,j,l} = 0 \qquad \Leftrightarrow \qquad n_{i,j} = 0$$

ie the simulated parameters always lead to the same employment status as in the data. However, because of random noise in (21), hours match the data only in expected value.

For the *unconditional* version, we always draw $w_{i,j,l}$ from (22), conditional on $\alpha_{i,j,l}$ and $\beta_{i,j,l}$, but not conditioning on whether $n_{i,j} = 0$ for $i = m, f$. Consequently, the employment rate will in general differ from that in the sample.

Both $Q^{1,S,u}$ and $Q^{1,S,c}$ take sample variation into account, but use posterior estimates for α and β directly, which will then reflect the population *in the sample*. However, we can generalize this process by also drawing $(\alpha, \beta)_{i,j,l}$ for $i = m, f$ directly from (22), again conditionally and unconditionally. This would lead to *superpopulation* versions $Q^{1,U,u}$ and $Q^{1,U,c}$. The intuition behind this is that we instead of looking at individuals who are in our sample, we suppose that (22) is valid and use it to draw conclusions about individuals *outside* the sample, also called the superpopulation.

Finally, note that Q is a random variable, and thus by using simulation we can approximate *credible intervals* (the Bayesian equivalent of confidence intervals) for statistics of interest. There are two potential sources of variation:

1. the posterior distribution, ie different posterior draws $l \in \mathcal{L}$, which is inherent in any estimation procedure,

2. the randomness of the finite sample of simulated values for each l.

We can asymptotically eliminate the second one by using $K > 1$ replications for each l, and use their average in (28). For a large K, we this behaves like an integral.

For practical purposes, we do not need all possible combinations of these operators. For posterior predictive checks that compare estimated quantities to our sample directly, we use $Q^{1,S,c}$ and $Q^{1,S,u}$, while for calculating aggregate statistics and counterfactual experiments we would use $Q^{K,U,u}$ for some large $K \gg 1$.

7 Conclusion

Possible extensions: policy experiments, e.g., varying labor income taxes. Lastly, it can account for children in the family when children are modeled as a public good.

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A Additional data tables

Tables 8, 9, 10 and 11 describe summary statistics of the data.

B Additional graphs and tables for results

Table 8: Different household types in the 2002/2002 wave

		obs	means	std dev
man works				
wage	man	384	2322.07	1151.66
	woman			
hourly wage	man	367	15.50	6.43
	woman			
non-labor income		786	483.49	680.58
age	man	393	49.38	7.72
	woman	393	47.04	7.85
woman works				
wage	man			
	woman	146	1013.70	709.54
hourly wage	man			
	woman	114	9.82	3.76
non-labor income		294	1293.20	768.49
age	man	147	54.49	7.64
	woman	147	49.25	7.10
both work				
wage	man	1197	2111.20	1036.09
	woman	1173	947.09	699.27
hourly wage	man	1.160	13.54	5.85
	woman	915	9.71	4.48
non-labor income		2426	277.30	511.00
age	man	1213	46.54	7.26
	woman	1213	43.85	7.04
neither works				
wage	man			
	woman			
hourly wage	man			
	woman			
non-labor income		326	1892.95	903.38
age	man	163	56.33	7.37
	woman	163	53.69	7.86

Notes: Households with and without kids. Total number of observations is 3832, i.e. 1916 couples. 1816 couples are married.

Table 9: Average daily time use 2012/2013

couple type		market work				home production										leisure	
		total		core		total		core		shop		other		child			
		h	m	h	m	h	m	h	m	h	m	h	m	h	m	h	m
both work	man	8	58	7	57	1	20	0	31	0	28	0	23	0	0	5	42
no kids	woman	7	31	6	34	2	35	1	29	0	48	0	19	0	0	5	54
both work	man	9	2	7	56	1	45	0	31	0	27	0	28	0	24	5	13
kids	woman	6	17	5	32	3	57	1	58	0	54	0	23	0	51	5	47
one works	man (works)	8	3	6	52	1	31	0	28	0	34	0	26	0	0	6	26
no kids	woman	0	7	0	5	5	16	3	11	1	16	0	46	0	0	10	38
	man	1	0	0	53	4	54	1	40	1	22	1	45	0	0	10	6
	woman (works)	7	15	6	24	2	19	1	11	0	50	0	16	0	0	6	26
one works	man (works)	9	1	7	47	1	37	0	26	0	22	0	29	0	26	5	22
kids	woman	0	15	0	13	7	1	3	57	1	16	0	36	1	30	8	44
	man	0	24	0	12	5	51	2	21	1	14	1	21	1	9	9	45
	woman (works)	7	38	6	32	2	45	1	21	0	33	0	19	0	41	5	37
no one works	man	0	15	0	12	4	10	1	20	0	59	1	25	0	0	11	35
no kids	woman	0	18	0	16	4	22	2	26	1	12	0	50	0	0	11	20
no one works	man	0	21	0	12	3	41	0	49	1	23	1	2	0	39	11	59
kids	woman	0	14	0	10	5	47	3	22	1	8	0	30	1	14	9	59

Notes: Figures show daily averages of various time use aggregates in hours (h) and minutes (m). In home production, shop denotes shopping, other denotes gardening and construction, and child denotes childcare.

Table 10: Different household types in the 2012/2013 wave

with and without kids		observations	means	std deviations
man works				
wage	man	225	2702.00	1194.61
	woman			
hourly wage	man	221	17.57	7.79
	woman			
non-labor income		450	553.78	730.48
age	man	225	49.54	7.10
	woman	225	46.99	7.62
woman works				
wage	man			
	woman	72	1698.61	1007.51
hourly wage	man			
	woman	72	13.22	6.62
non-labor income		144	1131.25	1004.55
age	man	72	52.89	7.73
	woman	72	49.44	7.16
both work				
wage	man	745	2539.20	1123.94
	woman	745	1424.36	774.37
hourly wage	man	742	16.00	7.00
	woman	743	12.59	5.46
non-labor income		1490	199.19	331.96
age	man	745	47.62	7.09
	woman	745	44.95	7.01
neither works				
wage	man			
	woman			
hourly wage	man			
	woman			
non-labor income		142	1713.38	740.09
age	man	71	54.14	9.06
	woman	71	50.68	9.01

Notes: Households with and without kids. Total number of observations is 2226, i.e. 1113 couples. 974 couples are married.

Table 11: Main source of income by household type

	household type				total
	both work	man works	woman works	no one works	
employment	83,3	84,5	44,9	0,6	73,5
self-employed/agriculture	13,6	9,2	4,1	0	10,8
pension	1,2	4,6	35,4	60,7	9,6
unemployment benefits	1,2	1	13,6	35	5
social security	0	0	0	0,6	0,1
other public support	0	0	0,7	0	0,1
capital income/property	0,3	0,5	0,7	1,8	0,5
family support/alimony	0	0	0	0,6	0,1

Notes: 2001/2002 sample. Together with missing values the columns add to 100%.

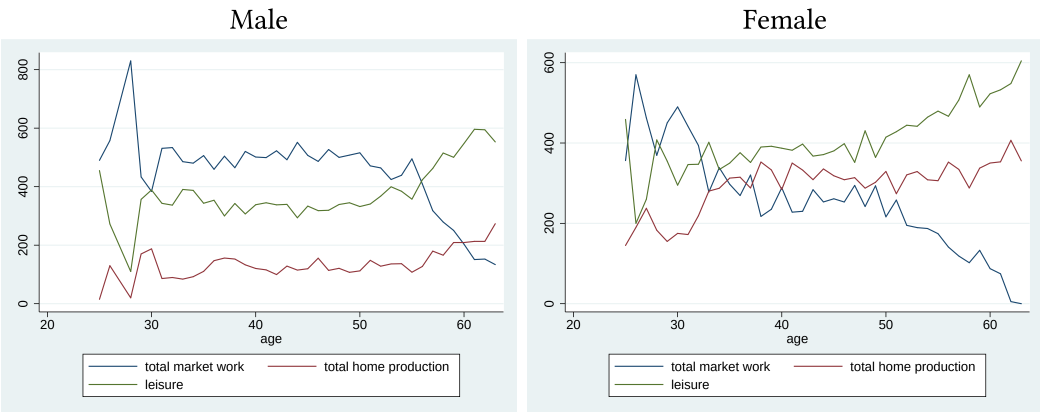

Figure 7: Average time-use by age and gender. 2001/2002 sample. The x-axis denotes average daily time-use in minutes.

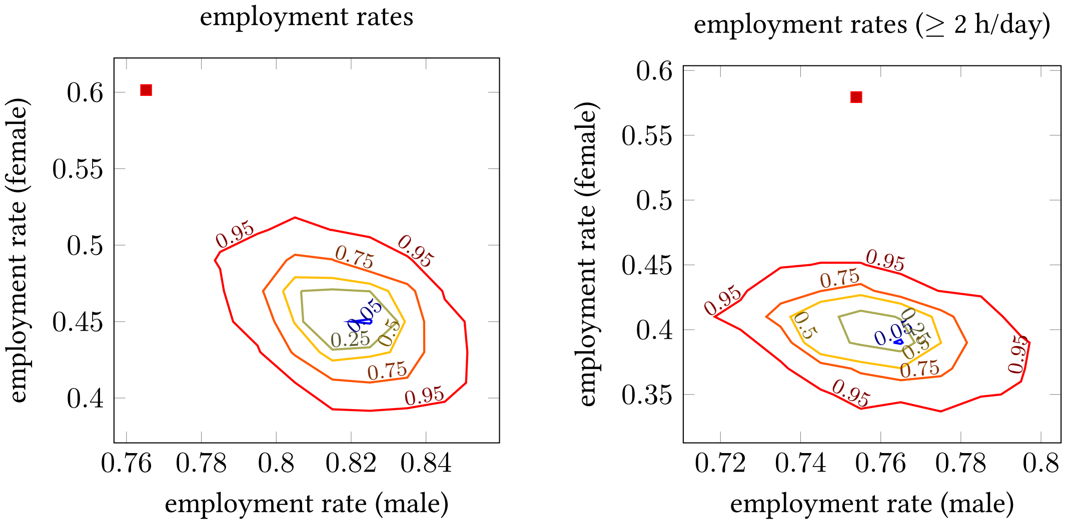

Figure 8: Observed and predicted employment rate by gender. Contour plot: highest posterior density regions for the indicated probabilities, red square: data. (a) employment threshold at 0 hours, (b) threshold at 2 hours/day.

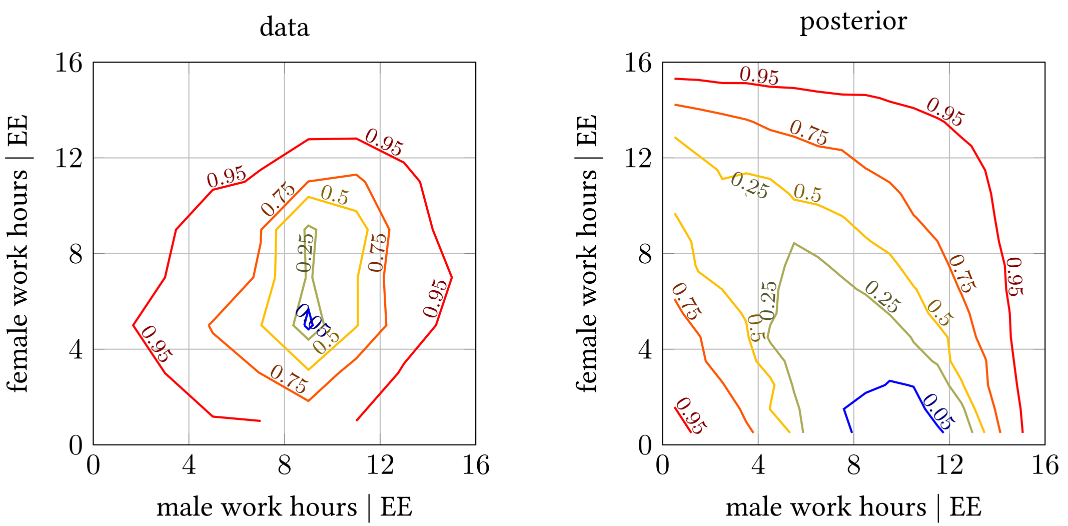

Figure 9: Observed and predicted distributions of working hours conditional on both members of the couples being employed. Contour plots show the highest posterior density regions for the indicated probabilities.

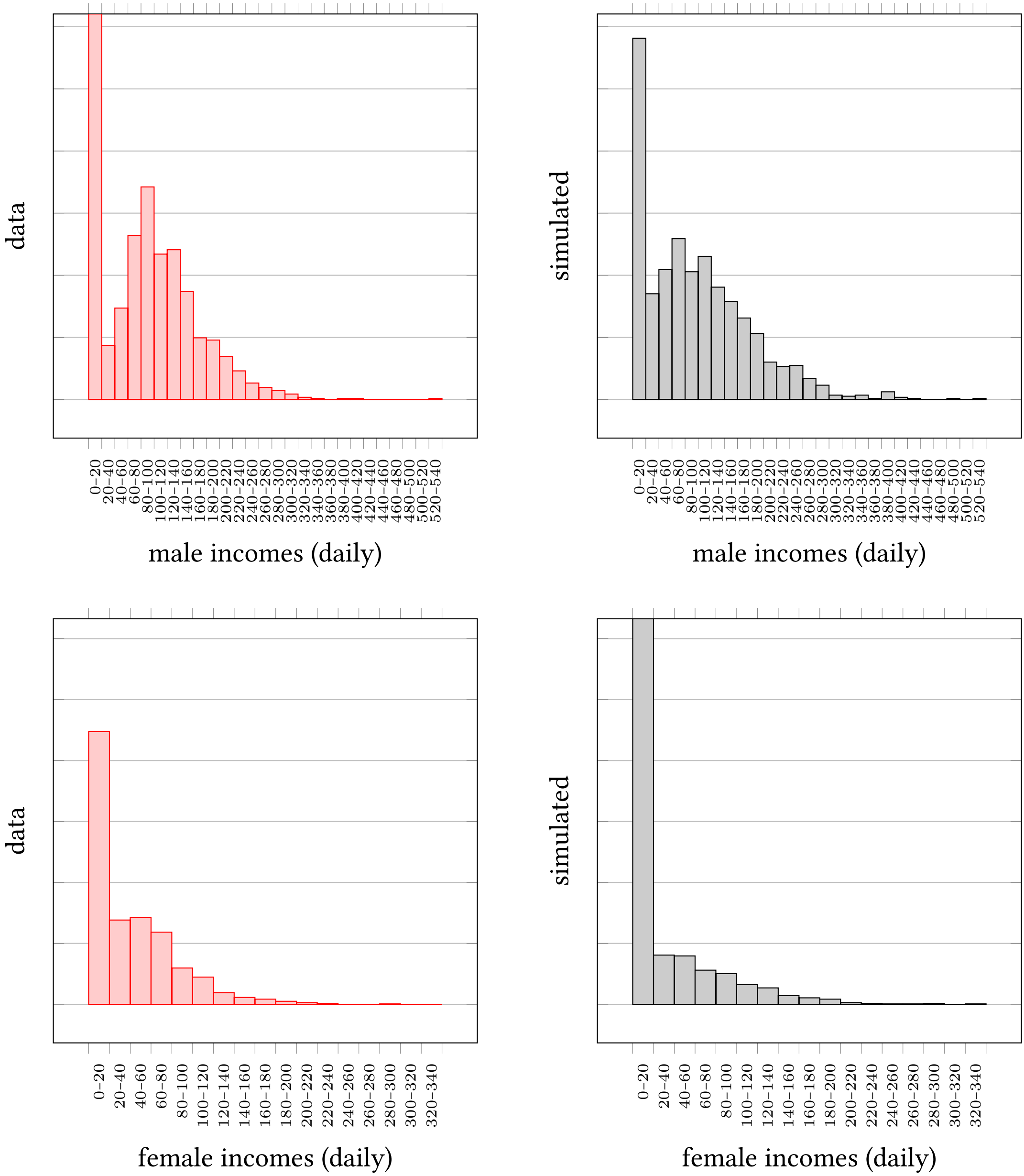

Figure 10: Earnings by gender. Left: data, right: simulation at posterior mean. Top: male, bottom: female.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.8	7.1	9.0	7.0	17	10.4	6.9	10.5	3.4	15	15.6	8.1	0	—	—	0
EN	50	14.4	9.1	—	0.0	15	10.7	7.1	10.2	2.8	33	16.3	7.8	0	—	—	1
NE	13	—	0.0	10.1	9.1	7	9.8	5.9	11.2	3.8	4	13.7	6.4	1	16.0	5.1	1
NN	5	—	0.0	—	0.0	0	—	—	—	—	3	13.1	3.9	0	—	—	2

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	1	-43	—	—	—	—	-60	-56	—	—	—	—
Δe	all	16	—	—	—	—	—	-8	—	—	—	—	—
Δn	all/E	-13	-42	22	-1	-14	-25	-57	-52	-61	-60	-58	-56
Δw	all/E	-2	-2	-1	-2	-2	-2	15	-0	23	18	15	12
$\Delta \ell$	all	-0	-31	55	16	-7	-19	16	-23	57	21	9	4
Δp	EE	25	—	—	—	—	—	25	—	—	—	—	—
Δn	EE	-5	-47	68	18	-7	-22	-54	-53	-53	-54	-55	-54
Δw	EE	-18	-33	-12	-15	-17	-20	17	-1	25	21	17	14
$\Delta \ell$	EE	6	-29	52	19	0	-10	38	-17	106	58	35	19
Δp	EN	10	—	—	—	—	—	10	—	—	—	—	—
Δn	EN	-17	-37	3	-5	-17	-26	—	—	—	—	—	—
Δw	EN	10	-2	16	13	10	7	—	—	—	—	—	—
$\Delta \ell$	EN	21	-21	87	45	18	1	2	-2	3	2	2	1
Δp	NE	-87	—	—	—	—	—	-87	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	-48	-35	-58	-52	-46	-44
Δw	NE	—	—	—	—	—	—	53	24	70	60	54	47
$\Delta \ell$	NE	6	-20	13	7	4	2	53	-11	159	88	54	29
Δp	NN	-31	—	—	—	—	—	-31	—	—	—	—	—
$\Delta \ell$	NN	3	-8	6	3	2	1	-0	0	0	-0	-0	-0

Table 12: Aggregating only α, for *both members* of the couple. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	$p_\%$	w_f	n_f	$p_\%$
EE	32	12.7	7.1	9.0	7.0	27	12.8	6.1	8.9	7.7	3	14.3	8.8	2	11.9	10.3	0
EN	50	14.4	9.1	—	0.0	3	13.0	7.5	8.7	1.5	46	14.6	8.0	0	—	—	1
NE	13	—	0.0	10.1	9.1	9	11.4	4.7	9.7	8.1	2	12.8	7.7	3	12.0	10.0	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	3	12.5	3.9	0	—	—	2

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	-5	-38	—	—	—	—	-5	-1	—	—	—	—
Δe	all	13	—	—	—	—	—	-5	—	—	—	—	—
Δn	all/E	-16	-38	9	-6	-15	-25	-0	1	-3	-1	-0	0
Δw	all/E	-1	-2	-0	-1	-1	-1	1	0	1	1	1	1
$\Delta \ell$	all	4	-27	59	19	-4	-13	1	-0	4	2	1	1
Δp	EE	20	—	—	—	—	—	20	—	—	—	—	—
Δn	EE	-17	-42	24	-2	-17	-27	4	1	10	8	5	3
Δw	EE	-2	-4	-0	-1	-2	-2	1	-1	2	2	1	1
$\Delta \ell$	EE	14	-23	62	27	9	-1	-3	-0	-7	-5	-4	-2
Δp	EN	9	—	—	—	—	—	9	—	—	—	—	—
Δn	EN	-14	-41	11	-2	-16	-26	—	—	—	—	—	—
Δw	EN	0	-1	1	0	-0	-0	—	—	—	—	—	—
$\Delta \ell$	EN	19	-25	87	44	16	-2	0	-0	0	0	-0	-0
Δp	NE	-65	—	—	—	—	—	-65	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	10	-1	22	16	10	5
Δw	NE	—	—	—	—	—	—	18	17	18	19	19	18
$\Delta \ell$	NE	4	-11	8	4	2	1	-13	-4	-19	-19	-17	-12
Δp	NN	-45	—	—	—	—	—	-45	—	—	—	—	—
$\Delta \ell$	NN	3	-9	6	3	2	1	-0	0	0	-0	-0	-0

Table 13: Aggregating only α, for *males only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

from						to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	16	11.0	7.1	10.2	3.4	15	14.8	9.8	1	10.9	7.3	0
EN	50	14.4	9.1	—	0.0	14	11.5	6.9	9.8	3.0	34	15.7	9.8	2	10.2	6.4	0
NE	13	—	0.0	10.1	9.1	3	11.5	1.8	9.9	5.3	1	—	—	8	10.8	6.1	2
NN	5	—	0.0	—	0.0	0	—	—	—	—	0	—	—	1	10.2	2.6	4

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	2	1	—	—	—	—	-46	-45	—	—	—	—
Δe	all	0	—	—	—	—	—	0	—	—	—	—	—
Δn	all/E	2	0	4	4	2	1	-46	-43	-50	-48	-46	-44
Δw	all/E	0	-0	0	0	0	0	9	2	13	11	10	8
$\Delta \ell$	all	-2	1	-4	-4	-2	-1	12	-20	46	15	6	2
Δp	EE	2	—	—	—	—	—	2	—	—	—	—	—
Δn	EE	-7	-4	-8	-10	-9	-7	-51	-50	-51	-52	-52	-51
Δw	EE	-11	-17	-8	-10	-11	-13	11	3	15	13	12	10
$\Delta \ell$	EE	6	-2	16	11	7	3	37	-17	104	56	33	18
Δp	EN	-1	—	—	—	—	—	-1	—	—	—	—	—
Δn	EN	7	-5	18	10	6	3	—	—	—	—	—	—
Δw	EN	7	1	11	9	7	6	—	—	—	—	—	—
$\Delta \ell$	EN	-10	-6	-11	-12	-12	-10	2	-1	2	2	1	1
Δp	NE	-4	—	—	—	—	—	-4	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	-35	-42	-29	-28	-32	-39
Δw	NE	—	—	—	—	—	—	5	2	7	6	6	5
$\Delta \ell$	NE	1	-1	1	1	0	0	45	-17	146	79	44	21
Δp	NN	6	—	—	—	—	—	6	—	—	—	—	—
$\Delta \ell$	NN	-0	1	-0	-0	-0	-0	1	-1	2	2	1	1

Table 14: Aggregating only α, for *females only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	26	13.2	7.6	8.5	7.8	5	13.2	9.5	2	8.5	10.2	0
EN	50	14.4	9.1	—	0.0	5	13.2	7.9	8.5	2.9	44	13.2	9.3	0	—	—	0
NE	13	—	0.0	10.1	9.1	4	13.2	2.5	8.5	8.1	0	13.2	3.6	9	8.5	9.5	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	1	13.2	1.9	0	—	—	3

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	4	-2	—	—	—	—	1	0	—	—	—	—
Δe	all	3	—	—	—	—	—	1	—	—	—	—	—
Δn	all/E	0	-0	1	1	0	0	0	0	0	1	1	0
Δw	all/E	-4	-100	48	16	-5	-26	-8	-100	38	10	-10	-29
$\Delta \ell$	all	-3	-2	-3	-3	-3	-3	-0	0	-1	-0	-0	-0
Δp	EE	7	—	—	—	—	—	7	—	—	—	—	—
Δn	EE	1	0	2	1	1	0	2	0	4	3	2	1
Δw	EE	4	-100	58	25	2	-20	-5	-100	42	13	-7	-26
$\Delta \ell$	EE	-0	0	-1	-0	-0	-0	-1	-0	-2	-2	-1	-1
Δp	EN	1	—	—	—	—	—	1	—	—	—	—	—
Δn	EN	1	-0	2	1	1	0	—	—	—	—	—	—
Δw	EN	-8	-100	41	11	-10	-29	—	—	—	—	—	—
$\Delta \ell$	EN	-1	-1	-1	-1	-1	-1	0	-0	0	0	0	0
Δp	NE	-15	—	—	—	—	—	-15	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	2	0	4	3	2	1
Δw	NE	—	—	—	—	—	—	-15	-100	27	1	-17	-34
$\Delta \ell$	NE	0	-1	1	0	0	0	-2	-0	-3	-4	-3	-2
Δp	NN	-14	—	—	—	—	—	-14	—	—	—	—	—
$\Delta \ell$	NN	0	-1	1	0	0	-0	0	0	0	0	0	0

Table 15: Aggregating *wages*, for *both members* of the couple. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	27	13.2	7.6	9.0	7.4	4	13.2	9.3	1	10.0	9.5	0
EN	50	14.4	9.1	—	0.0	3	13.2	8.1	8.7	2.0	47	13.2	9.3	0	—	—	0
NE	13	—	0.0	10.1	9.1	3	13.2	2.1	9.5	8.1	0	—	—	10	10.3	9.2	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	1	13.2	1.9	0	—	—	4

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	4	-2	—	—	—	—	-4	-1	—	—	—	—
Δe	all	3	—	—	—	—	—	-4	—	—	—	—	—
Δn	all/E	0	-0	1	1	0	0	0	0	1	0	0	0
Δw	all/E	-4	-100	48	16	-6	-26	1	0	1	1	1	0
$\Delta \ell$	all	-3	-2	-3	-3	-3	-3	1	-0	2	2	1	0
Δp	EE	2	—	—	—	—	—	2	—	—	—	—	—
Δn	EE	0	0	1	1	0	0	1	-0	4	2	1	1
Δw	EE	4	-100	58	25	2	-20	1	1	1	1	1	1
$\Delta \ell$	EE	-0	0	-0	0	0	0	-1	-0	-1	-1	-1	-1
Δp	EN	4	—	—	—	—	—	4	—	—	—	—	—
Δn	EN	0	-0	0	0	0	0	—	—	—	—	—	—
Δw	EN	-8	-100	41	11	-10	-29	—	—	—	—	—	—
$\Delta \ell$	EN	-0	-0	-0	-0	-0	-0	-0	0	-0	-0	-0	-0
Δp	NE	-16	—	—	—	—	—	-16	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	1	-0	3	2	1	1
Δw	NE	—	—	—	—	—	—	2	1	2	2	2	1
$\Delta \ell$	NE	0	-1	1	0	0	0	-2	-1	-2	-2	-2	-2
Δp	NN	-12	—	—	—	—	—	-12	—	—	—	—	—
$\Delta \ell$	NN	0	-1	1	0	0	0	-0	0	0	-0	-0	-0

Table 16: Aggregating *wages*, for *males only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	27	12.8	7.3	8.5	7.7	3	13.6	9.0	2	8.5	9.9	0
EN	50	14.4	9.1	—	0.0	4	13.1	8.0	8.5	2.3	45	14.5	9.1	0	—	—	0
NE	13	—	0.0	10.1	9.1	2	11.7	1.7	8.5	8.4	0	—	—	11	8.5	9.3	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	0	—	—	0	—	—	5

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	-0	0	—	—	—	—	5	1	—	—	—	—
Δe	all	-0	—	—	—	—	—	4	—	—	—	—	—
Δn	all/E	-0	0	-0	-0	-0	-0	0	0	0	0	0	0
Δw	all/E	0	0	0	0	0	0	-8	-100	38	10	-10	-29
$\Delta \ell$	all	0	0	0	0	0	0	-1	0	-3	-2	-1	-1
Δp	EE	5	—	—	—	—	—	5	—	—	—	—	—
Δn	EE	0	0	1	1	0	0	0	0	1	1	1	0
Δw	EE	0	0	0	0	0	0	-5	-100	42	13	-7	-26
$\Delta \ell$	EE	-0	0	-0	-0	-0	-0	-0	0	-1	-0	-0	-0
Δp	EN	-4	—	—	—	—	—	-4	—	—	—	—	—
Δn	EN	0	-0	1	1	0	0	—	—	—	—	—	—
Δw	EN	0	0	1	1	0	0	—	—	—	—	—	—
$\Delta \ell$	EN	-1	-0	-1	-1	-1	-1	0	-0	0	0	0	0
Δp	NE	2	—	—	—	—	—	2	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	0	0	1	1	0	0
Δw	NE	—	—	—	—	—	—	-15	-100	27	1	-17	-34
$\Delta \ell$	NE	0	-0	0	0	0	-0	-0	-0	-1	-0	-0	-0
Δp	NN	-3	—	—	—	—	—	-3	—	—	—	—	—
$\Delta \ell$	NN	0	-0	0	0	-0	-0	0	-0	0	0	0	0

Table 17: Aggregating *wages*, for *females only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	17	—	—	—	—	15	13.2	7.3	0	—	—	0
EN	50	14.4	9.1	—	0.0	20	—	—	—	—	29	13.2	6.8	0	—	—	1
NE	13	—	0.0	10.1	9.1	5	—	—	—	—	8	13.2	6.5	0	—	—	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	4	13.2	4.2	0	—	—	1

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	13	-55	—	—	—	—	-91	-93	—	—	—	—
Δe	all	20	—	—	—	—	—	-9	—	—	—	—	—
Δn	all/E	-6	-52	48	13	-8	-25	—	—	—	—	—	—
Δw	all/E	-4	-100	48	16	-5	-26	—	—	—	—	—	—
$\Delta \ell$	all	-8	-60	76	4	-23	-34	28	-95	136	42	10	-10
Δp	EE	29	—	—	—	—	—	29	—	—	—	—	—
Δn	EE	—	—	—	—	—	—	—	—	—	—	—	—
Δw	EE	—	—	—	—	—	—	—	—	—	—	—	—
$\Delta \ell$	EE	—	—	—	—	—	—	—	—	—	—	—	—
Δp	EN	12	—	—	—	—	—	12	—	—	—	—	—
Δn	EN	-26	-46	-12	-19	-25	-33	—	—	—	—	—	—
Δw	EN	-8	-100	42	11	-10	-29	—	—	—	—	—	—
$\Delta \ell$	EN	38	-51	154	63	27	7	2	-100	31	7	-7	-18
Δp	NE	-100	—	—	—	—	—	-100	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	—	—	—	—	—	—
Δw	NE	—	—	—	—	—	—	—	—	—	—	—	—
$\Delta \ell$	NE	—	—	—	—	—	—	—	—	—	—	—	—
Δp	NN	-66	—	—	—	—	—	-66	—	—	—	—	—
$\Delta \ell$	NN	0	-100	19	1	-8	-15	2	-100	31	8	-6	-17

Table 18: Aggregating *wages and preferences*, for *both members* of the couple. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	w_f	n_f	$p_{\%}$	w_m	n_m	$p_{\%}$	w_f	n_f	$p_{\%}$
EE	32	12.7	7.1	9.0	7.0	26	13.2	6.2	9.0	7.8	5	13.2	8.8	1	13.9	10.8	0
EN	50	14.4	9.1	—	0.0	4	13.2	7.4	8.9	2.5	46	13.2	7.9	0	—	—	1
NE	13	—	0.0	10.1	9.1	10	13.2	5.1	10.1	8.2	3	13.2	7.8	1	13.7	10.2	0
NN	5	—	0.0	—	0.0	0	—	—	—	—	4	13.2	4.2	0	—	—	1

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	1	-48	—	—	—	—	-10	-3	—	—	—	—
Δe	all	19	—	—	—	—	—	-9	—	—	—	—	—
Δn	all/E	-15	-43	14	-5	-16	-24	-1	1	-4	-2	-1	-0
Δw	all/E	-4	-100	48	17	-5	-26	1	1	2	2	1	1
$\Delta \ell$	all	1	-53	73	16	-9	-22	3	-1	7	4	2	1
Δp	EE	25	—	—	—	—	—	25	—	—	—	—	—
Δn	EE	-14	-48	43	4	-16	-28	6	1	13	11	8	5
Δw	EE	4	-100	58	25	2	-20	3	1	4	4	4	3
$\Delta \ell$	EE	14	-54	85	28	3	-10	-5	-0	-10	-8	-6	-3
Δp	EN	15	—	—	—	—	—	15	—	—	—	—	—
Δn	EN	-15	-43	8	-3	-15	-26	—	—	—	—	—	—
Δw	EN	-8	-100	41	11	-10	-29	—	—	—	—	—	—
$\Delta \ell$	EN	23	-48	125	40	8	-4	-0	-0	-0	0	-0	-0
Δp	NE	-89	—	—	—	—	—	-89	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	12	-3	33	20	11	5
Δw	NE	—	—	—	—	—	—	35	39	33	33	35	37
$\Delta \ell$	NE	-0	-100	18	0	-9	-15	-17	-6	-18	-22	-21	-18
Δp	NN	-73	—	—	—	—	—	-73	—	—	—	—	—
$\Delta \ell$	NN	0	-100	19	1	-8	-15	-1	-0	1	-0	-1	-2

Table 19: Aggregating *wages and preferences*, for *males only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

	from					to EE					to EN			to NE			to NN
	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	w_f	n_f	$p_\%$	w_m	n_m	$p_\%$	w_f	n_f	$p_\%$
EE	32	12.7	7.1	9.0	7.0	13	13.2	6.8	11.0	2.9	18	13.2	10.2	1	11.2	6.9	0
EN	50	14.4	9.1	—	0.0	12	13.2	6.4	10.4	2.8	35	13.2	10.1	2	10.5	6.2	0
NE	13	—	0.0	10.1	9.1	4	13.2	2.8	10.0	4.5	1	13.2	3.6	6	11.1	6.0	1
NN	5	—	0.0	—	0.0	0	—	—	—	—	1	13.2	2.2	1	10.4	2.7	3

		male (% change)						female (% change)					
	group	mean	std	q20	q40	q60	q80	mean	std	q20	q40	q60	q80
Δn	all	7	-1	—	—	—	—	-56	-49	—	—	—	—
Δe	all	4	—	—	—	—	—	-11	—	—	—	—	—
Δn	all/E	3	0	6	5	3	2	-50	-43	-59	-56	-52	-47
Δw	all/E	-4	-100	48	16	-5	-26	15	3	20	18	16	13
$\Delta \ell$	all	-5	-1	-8	-8	-7	-5	18	-59	93	44	10	-10
Δp	EE	-6	—	—	—	—	—	-6	—	—	—	—	—
Δn	EE	-14	-10	-14	-16	-17	-15	-56	-51	-60	-59	-57	-55
Δw	EE	4	-100	58	25	2	-20	18	5	24	22	20	16
$\Delta \ell$	EE	12	-6	35	21	12	6	49	-58	169	84	43	14
Δp	EN	10	—	—	—	—	—	10	—	—	—	—	—
Δn	EN	9	-7	24	13	7	3	—	—	—	—	—	—
Δw	EN	-8	-100	41	11	-10	-29	—	—	—	—	—	—
$\Delta \ell$	EN	-12	-8	-13	-14	-15	-14	2	-100	31	7	-7	-18
Δp	NE	-24	—	—	—	—	—	-24	—	—	—	—	—
Δn	NE	—	—	—	—	—	—	-36	-42	-32	-29	-32	-39
Δw	NE	—	—	—	—	—	—	8	4	10	9	8	7
$\Delta \ell$	NE	1	-2	2	1	1	0	54	-47	211	86	43	20
Δp	NN	-4	—	—	—	—	—	-4	—	—	—	—	—
$\Delta \ell$	NN	0	0	0	0	-0	0	2	-100	31	8	-6	-17

Table 20: Aggregating *wages and preferences*, for *females only*. Top: comparing baseline and counterfactual outcomes for groups of couples by employment. Bottom: percentage changes between the baseline and the counterfactual statistics. Variables: p: population share, w: wage (observed), n: hours worked, e: employment, ℓ: leisure hours.

C 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
Y, Y_i	total income for household, individual wage incomes
	model characterization
superscripts n, c	*non-cooperative* and *cooperative* models
ν_i	share of leisure out of $T_i - n_i$ (6) and (6)
ϕ_i	key parameter that governs market time choice, (9) and (16)
	cross-sectional and stochastic setup
Δ	duration of measured time block
X_i	individual covariates (sex, age)
B	regression coefficient on individual covariates, (22)
Σ	covariance matrix for cross-sectional parametric distribution, (22)
	predictions
l	index of posterior draws
$q(\dots)$	statistic for prediction
G	population cross-sectional measure of covariates

D Common algebraic form for market hours

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

$$\max_{0 \leq n \leq T} (\tilde{M} + nw)(T - n)^{\phi} \tag{29}$$

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

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

Consequently, considering the constraint, the solution to (29) is

$$n = \begin{cases} 0 & \text{if } Tw \leq \phi\tilde{M} \\ \frac{T-\phi\tilde{M}/w}{1+\phi} & \text{otherwise.} \end{cases} \tag{30}$$

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.

E MCMC diagnostics

F Source code

Source code for the project is available at NOT YET PUBLIC.

We also use the following libraries, all of which are written by the authors and available under open-source licenses, for estimation:

- https://github.com/tpapp/IndirectLikelihood.jl for organizing the simulation framework for building the indirect posterior,
- https://github.com/tpapp/DynamicHMC.jl for posterior sampling,
- https://github.com/tpapp/ContinuousTransformations.jl for domain transformations for the posterior sampler,
- https://github.com/tpapp/MCMCDiagnostics.jl for MCMC diagnostics.

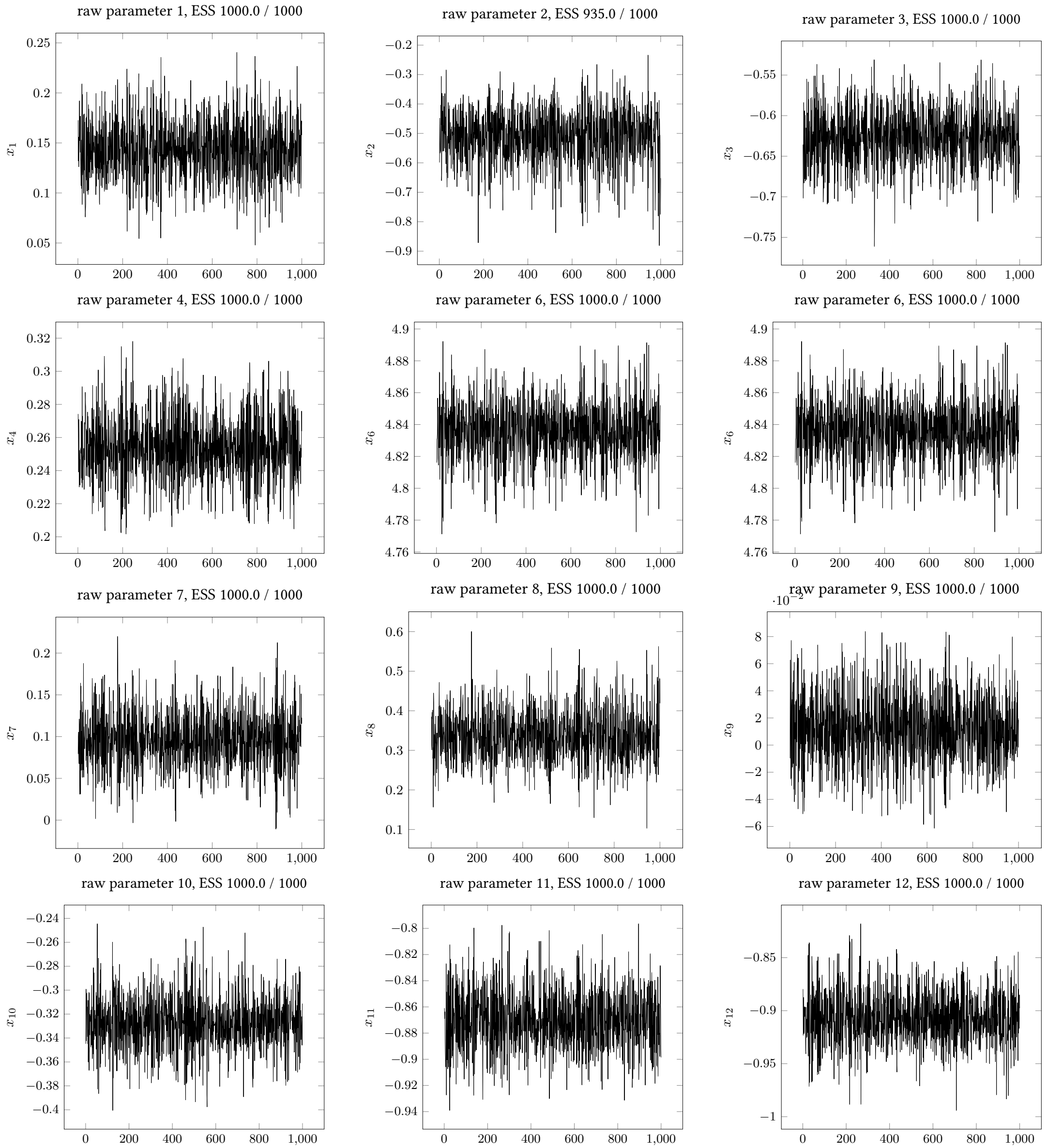

Figure 11: Posterior chain components and effective sample sizes.