Allocating Time as a Couple: Effects of Relative Wages and Gender Role Bias*

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Abstract

I study how gender role bias affects the time allocations of heterosexual working couples in labor, home production, and leisure, and the ramifications for distributional effects of policies that change effective wages. Using detailed time use data from Mexico and the U.K., I document that among working couples in both countries, as a female's relative wage increases, her relative labor hours decrease, and her relative home production hours increase. The pattern is seemingly puzzling but it can be rationalized if couples face disutility for breaking a social norm as females' share of household earnings increases. I then build a structural household model that incorporates gender role bias. Fitting the model to the U.K. data on working couples, I find that on average, disutility arising from gender role bias starts increasing when a female's earning share exceeds 0.45, that is, when she is nearly the breadwinner. Furthermore, I construct a measure of household-level bias using responses to survey questions on bias, and find that in more biased households, the disutility starts increasing when the female's earning share is lower. Using the model, I predict the effects of a fiscal policy that disproportionately increases females' effective wages. In particular, I find that when a given policy increases females' wages by 10 percent, the policy's effect on female labor supply is overestimated by 5 percentage points if gender role bias is not taken into account.

Keywords: Household decision, intra-household gender gap, labor supply, home production.

JEL Codes: D12, D13, D31, I31, J16, J22.

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1 Introduction

It is well documented that pronounced gender differences exist in labor markets in wages, labor force participation rates, and labor hours. For instance, on average, males in OECD countries spend 1.7 hours per day more on paid work and 2.1 hours less on unpaid work than females.[1] Focusing on the gender gap in labor hours and wages which directly affects individual's welfare, I document a puzzling relationship between females' wages and hours worked relative to males' in Mexico and the U.K. In both countries, females increase their labor share in home production relative to their male partners' when their relative wages increase. To rationalize this counterintuitive pattern, I suggest that gender role bias influences households' time allocation decisions and show that a measure of gender role bias helps explain the data. I then develop a structural household model with gender role bias to estimate the distributional effects of a fiscal policy that changes females' effective wages. I find that ignoring gender role bias overestimates the effect of a 10-percent increase in female wages on female labor supply by five percentage points.

The causes and consequences of gender differences in labor market outcomes are widely recognized as an important research area to promote gender equality and inclusive growth.[2] The literature has extensively studied gender differences in labor market participation rates, hours worked, and wages, but intra-household gender gaps have received less attention.[3] In this paper, I highlight the importance of accounting for gender role bias to accurately evaluate policies aimed at resolving gender discrepancies in labor supply through wages. For instance, policies that provide tax benefits to secondary earners are expected to disproportionately increase female labor supply because most secondary earners are female. Such policies' effectiveness will be partially offset if household decisions reflect gender role bias.[4]

To provide evidence that gender role bias affects couples' time allocation across countries, I use two panel survey data sets, the Mexican Family Life Survey (MxFLS, 2002-2009) and the British Household Panel Survey (BHPS, 1994-2004). These data sets observe all household members rather than one representative member, which allows for direct measurement of couples' relative time allocation in a household, instead of relying on across-household variations as previous studies have done. While the puzzling relationship between a female's relative time and wages is qualitatively the same across countries, I find the magnitude of the correlations is higher in Mexico than in

[1] Source: The World Bank (2019), OECD Statistics Time Use (2006 - 2018).

[2] The United Nations lists them among its primary Sustainable Development Goals. There are both economic and social benefits of reducing gender gaps in labor markets. For example, increasing female labor force participation rates is a way to empower females (Heath, 2014) which is a key in economic development (Duflo, 2012) and in promoting growth if human capital is a driver of the growth (Doepke and Tertilt, 2014). Also, Aizer (2010) finds decreasing wage gaps reduces violence against women.

[3] The main challenges come from data availability. Most time use surveys, including ATUS, collect the information of one representative household member rather than all household members; PSID collects information from all members but is vague on the definitions of activities.

[4] According to the World Value Survey (2010-14), gender role bias exists across many countries. For example, 43.3% of respondents from Mexico and 12.4% from the U.S. believe it is a problem if wives earn more income than their husbands. The survey result for the U.K. for this question is not available. However, based on answers to other questions in the World Value Survey, I expect a response of the U.K. to be similar to that of the U.S.

the U.K. Furthermore, according to Gender Social Norms Index, households in Mexico have a higher degree of bias than those in the U.K., as measured by the share of households that agree with gender-biased statements in each country.[5] This cross-country difference is consistent with a conjecture that gender role bias is, at least in part, responsible for generating the empirical pattern.

Furthermore, to control for contextual differences other than bias that may explain the observed differences across countries, I also explore how households within a country — the U.K. in this case — behave differently depending on their degree of bias. I first build a Gender Bias Index (GBI) similar to that in Goussé et al. (2017) to measure household-level bias for the U.K. households using survey questions on social norms and a principal component analysis. Equipped with this measure, I find that females' labor earning shares are less elastic to their wage shares when couples are more biased.

Based on the empirical patterns, I develop a household decision model that accounts for gender role bias, which I use to quantify the effect of wage changes on working couples' labor supply. In contrast with the empirical patterns, canonical household decision models including Blundell et al. (2005) predict that a share of a female's time in labor should increase and that of home production should decrease as a share of her wage increases.[6] In this paper, however, gender role bias is modeled such that couples prefer that females earn less than certain shares of total household income. Once females' earning shares exceed household-specific thresholds, disutility increases as females' earning shares increase. Consequently, when a household collectively decides how much time each member invests in labor, home production, and leisure, an increase in a female's wage share incentivizes her to work and increases her relative labor hours until her earning share exceeds the threshold. Once her earning share exceeds the threshold, gender role bias discourages her from working by increasing disutility from work. Accordingly, her relative labor hours decrease and her home production hours increase, which is consistent with observed empirical patterns.

I estimate the model using the U.K. households from which I can exploit information on the degree of bias for each household, using the constructed GBI. The estimation result shows that on average, gender role bias increases couples' disutility once females' earning shares are above 0.45. The predicted mean threshold complements Bertrand et al. (2015)'s argument that there is a social norm against female breadwinners. Furthermore, I find that disutility from gender role bias is triggered at lower thresholds for more biased households. This is intuitive as it implies that there is disutility for high-bias couples when females earn much less than males but not for low-bias households. In terms of individual preferences other than gender role bias, I find that females value the output of home production more than males, which is consistent with existing studies on household decisions such as Cherchye et al. (2012).

Given the estimates, I investigate the policy implications of gender role bias, focusing on quanti-

[5] Gender Social Norms Index uses data from the World Value Survey (2005-2014). More details on Gender Social Norms Index is in section 3. In addition to the survey, Jayachandran (2019) finds that the gender norms are stronger in developing countries than in developed countries. There can be many reasons why countries display different degrees of bias, including different historical backgrounds as proposed by Alesina et al. (2013).

[6] This is true even when the model allows for heterogeneous preferences and home production technology like Cherchye et al. (2012), and is dynamic like Lise and Yamada (2018) and Verriest (2019).

fying predicted policy effects. To do so, I evaluate fiscal policies that encourage females to increase their labor supply by increasing their effective wage. Examples of such fiscal policies include imposing a gender-based tax system where tax rates are determined by gender or a shift in the tax filing system from joint to single filing.[7] The latter is expected to disproportionately increase females' effective wages because it decreases the marginal tax rates of secondary earners, most of whom are female. As expected, the model predicts that females' labor hours would increase when their wages increase. However, I find that the structural model that disregards gender bias for the policy evaluation overestimates the magnitude of the increase by 5 percentage points. This emphasizes the importance of incorporating gender role bias in a model for quantitatively accurate policy predictions.

This paper complements the literature on gender role bias and labor supply by documenting new empirical patterns in both a developed country and a developing country that suggest gender role bias is important when couples make labor supply decisions.[8] Fernandez (2013) and Fernandez et al. (2004) investigate the role of cultural changes and social norms in increasing female labor force participation rates observed over the last century in the U.S. Blau et al. (2020) evaluates cultural effects on gender division of labor among U.S. immigrants. Hyun (2019) finds that in Japan, households are irresponsive to an economic shock and attributes it to social norms against working females. While these papers focus on developed countries, Jayachandran (2015) and Jayachandran (2019) focus on the impact of gender bias or cultural barriers on gender inequality in developing countries. Bertrand et al. (2015) is closest to this paper where it argues that in the U.S., the wife spends more time in home production if her potential income exceeds her husband's, a result attributed to gender role bias. However, in addition to the contextual differences between that paper and this paper, Bertrand et al. (2015) focuses on how couples' behavior changes according to the gender of the breadwinners, while I explore how couples' behavior changes as relative hourly wages continuously change, thus offering richer analyses.

This paper also contributes to the literature on household decisions. More specifically, my model allows for corner solutions and builds on collective household models with home production stemming from Blundell et al. (2005) where home-produced goods are public and non-marketable.[9]

[7] Borella et al. (2019) predicts that eliminating marriage-related benefits increases the female labor force participation rate. Kaygusuz (2010) finds the Economic Recovery Tax Act of 1981 and the Tax Reform Act of 1986 have contributed to the rise in labor force participation of married women in the U.S. from 1980 to 1990 by decreasing the marginal tax rate faced by second earners. Nikolka (2016) emphasizes the importance of understanding the effects of second earner income taxation on labor supply decisions to promote female labor force participation. The provision of such tax benefits would imply an increase in females' effective wages.

[8] There are papers that evaluate how gender role bias relates to individuals' choices in areas other than labor supply. For example, Bertrand et al. (2016) argues social attitudes towards working women might contribute to low marriage rates among skilled women. Foged (2016) studies how gender role bias affects couples' migration choices by making earnings potentials different across gender. Based on experimental evidence, Bursztyn et al. (2018) proposes misperceived social norms as a potential source of labor market frictions, and Bursztyn et al. (2017) argues that strong gender role bias influences women to avoid career-enhancing activities in order to be more desirable brides in the marriage market. From a perspective of labor demand, Albanesi and Olivetti (2009) proposes a theoretical framework where women are offered lower wages because firms believe women do more home production than men.

[9] Collective models of Chiappori (1988) and Apps and Rees (1988) study labor supply choices of households without home production. Cherchye et al. (2012) applies Blundell et al. (2005) to Dutch data while restricting the

This paper contributes to the literature by proposing a more general model that can rationalize the empirical patterns by introducing gender role bias in the model.

Finally, this paper adds to the literature on fiscal policies targeting gender inequality in the labor market. Alesina et al. (2011) theoretically analyzes the effects of potential gender-based tax policy and argues that the policy has distributional benefits. Gayle and Shephard (2019) proposes the optimal tax design taking into account its impact on marriage markets and family decisions. Ichino et al. (2019) finds that households react to tax changes differently depending on the degree of each household's gender role bias. This paper extends the literature by highlighting the importance of incorporating gender role bias in policy evaluations.

The rest of the paper is organized as follows. The data and time allocation patterns of Mexican and the U.K. households are described in Sections 2 and 3. Given these data patterns, a household model with gender role bias is introduced in Section 4, and the parametric specification of the model and estimation strategy is presented in Section 5. The estimation results are discussed in Section 6. Given the parameter estimates, I analyze the effect of a policy that provides financial incentives to households to reduce gender gaps in time allocation in Section 7. Finally, I conclude the paper in Section 8.

2 Data

I focus on Mexico and the United Kingdom for the empirical analyses. For both countries, I use longitudinal, household-level panel survey data called the Mexican Family Life Survey (MxFLS, 2002-2009) and the British Household Panel Survey (BHPS, 1994-2004). MxFLS collects data every 3 to 5 years with a maximum of three observations per household, while BHPS data is collected every year.

The key feature of MxFLS and BHPS is that time use of all household members is observed, and that leisure and home production time are distinguishable from each other.[10] MxFLS is distinct from other time use data sets because it is collected in a developing country rather than developed countries. Time-use data is available in the main MxFLS dataset where respondents report hours spent on 11 activities, including sleeping, reading, cooking, taking care of elderly or sick or children, and using the internet over the past week.

Meanwhile, the main BHPS dataset does not contain actual hours spent on leisure or home production, but several potential predictors of time use. These include respondents' regular weekly hours of paid work and housework, participation frequency in various leisure activities, and responsible members for each housework activity within the household. The BHPS provides time use data for waves 4 to 14 (1994-2004) where the amount of time spent in each category of activities is calibrated using information from a smaller panel survey with a time diary and the same set of survey questions from the same respondents.[11]

sample to working couples with children.

[10]Another dataset with this feature is Japanese Panel Survey of Consumers.

[11]Details on the complementary time use data are in Kan and Gershuny (2006).

Using the detailed time use information, I categorize time uses into three categories, leisure, labor, and home production. Sleeping is included in leisure, and commuting time to work is included in labor.[12] Also, I categorize time spent cooking, doing other house chores, and caring for other household members as home production. Because I focus on nuclear households, time spent caring for other household members is equivalent to time spent caring for children.

In addition to time use information, I also observe household characteristics such as total earnings and family composition, and individual characteristics such as age, education level, and employment status in both countries. Individuals also report hourly wages if paid hourly (in the BHPS) or if they know the composition of weekly earnings (in the MxFLS) by categories including wages or salary, commissions and tips, or transportation. For those without hourly wage information, I calculate hourly wages by dividing their gross income by reported labor hours.

Finally, the final sample is selected according to several criteria for both countries. A household is excluded if it is an extended household, if the necessary information is missing such as age, education, number of kids, total expenditure, region, and time use, or if female (male) member spends zero time in home production (labor).[13] The number of selected households as each selection criteria is imposed is reported in Tables 7 and 8. As Table 7 shows, many households in Mexico are excluded due to the first criterion, as there are many extended families. The summary statistics of selected households are in Tables 9 and 10. As a result, I end up with 1560 Mexican households and 2013 British households for the analysis.

3 Intra-household gender gaps in time allocations and wages

In this section, I provide suggestive empirical evidence that gender role bias interacts with relative wages and affects the division of labor inside the family. To do so, I document couples' time allocation patterns in Mexico and the U.K. using the subsample of 2921 working couples or households where both female and male members spend a strictly positive amount of time in leisure, labor, and home production.

For the analyses, I impute hourly wages based on observable characteristics for some observations in Mexico if wage information is missing while positive labor hours are reported. For the imputation, I correct for a possible sample selection bias in estimating wages for self-employed following Bourguignon et al. (2007).[14] Variables in the selection equation that are excluded from the second stage include a dummy on whether couples have children, the number of females and males in the household, spouse's age and education level, and a dummy for whether the spouse works in the formal sector. An individual works in the formal sector if his/her employer provides

[12] If an individual reports zero sleeping hours, we consider the data as erroneous and drop relevant observation. Refer to Appendix A for further details on time use data.

[13] The extended households are excluded because of complementarity and substitutability in time use amongst adults, especially of same gender, which complicate how we should build household's optimization problems.

[14] I use "selmlog" command provided by the authors and conduct a variant of the Dubin and Mcfadden (1984) correction method suggested in Bourguignon et al. (2007). Refer to Appendix B for more details.

the social security following the conventional definition.[15] For the U.K. households, I use imputed hourly wage information provided by the BHPS in complementary data.[16] For both countries, the results are robust to wage imputations as they are qualitatively unchanged even if I exclude households with missing wage information. Results excluding households with missing wage information are available in appendix E. Finally, throughout the paper, "wage" means hourly wage rates and "earnings" means weekly labor earnings.

I first document how couples allocate time given hourly wage differences by running the following panel regression for a country c at time t and household i

$$y_{cit} = \beta_0 + \beta_1 x_{cit} + \beta_2 x_{cit}\mathbb{I}(\text{U.K.}) + \beta' Z_{cit} + f_{ci} + f_{ct} + e_{cit} \tag{1}$$

where y_{cit} is female time shares (female/(female + male)) in labor or home production, x_{cit} is female wage shares, $\mathbb{I}(\text{U.K.})$ is a country dummy with value 1 if i is the U.K. household, and Z_{cit} is a vector of controls that includes the following variables: female and male education levels, number of children, average age of children, household income level (measured by total consumption in Mexico and by total earnings in the U.K.), and sex of the breadwinner where breadwinners are the members of each household earning the highest income. Finally, f_{ci}, f_{ct} are household and time fixed effects respectively, and e_{cit} is an error term. According to canonical models without gender role bias, we would expect β_1 to be positive if the dependent variable is a female's labor share and negative if the dependent variable is her home production time share.

The regression results are depicted in Figure 1 where I plot a predicted female's time share in labor and home production as a function of her wage share for each country.[17] Values are conditioned on the control variables and centered around mean. They show that there is a positive correlation between female wage shares and home production time shares, and a negative correlation between wage shares and labor time shares in both countries. The patterns are inconsistent with canonical models because they imply a female member spends less time in activities where her opportunity costs are lower as compared to the spouse's. Furthermore, the pattern cannot be explained by standard collective household models where a household is maximizing the weighted average of female and male utilities, and the weight represents female's bargaining power. If the bargaining power is independent of relative wages, the standard collective household models would predict female's labor (home production) shares to increase (decrease) as her wage shares increase because her opportunity cost has increased. If female's bargaining power increases with her relative wages, then parametric assumptions on the home production technology become important. If females value home production more than males, then more goods are produced at home as female wage shares increase. Assuming the technology is constant returns to scale as commonly assumed, expenditure shares of both female's and male's time should increase. However, as her wage shares

[15] Time allocation patterns for households excluding those with imputed wages are available in the appendix. The time patterns do not change when households with imputed wages are excluded.

[16] Some wage information is missing even for working individuals.

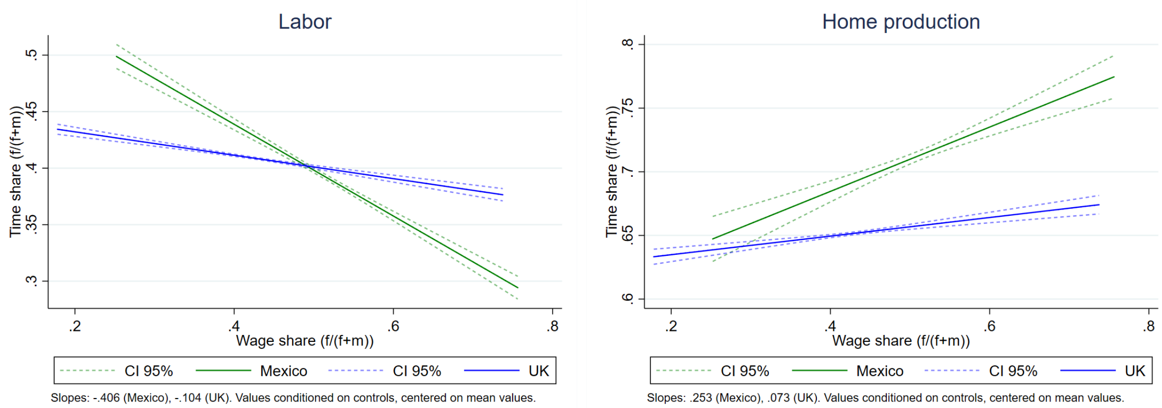
[17] Full regression results are available in Appendix D Table 14.

increase, this implies female's relative home production time should decrease. This is opposite of what we see in Figure 1.

In other words, Figure 1 suggests that there is a factor that deters females from increasing their labor and rather increases their time spent on home production. Furthermore, the slopes are steeper in Mexico than in the U.K., which implies the factor generating the pattern is stronger in Mexico than in the U.K. One candidate explanation is gender role bias where couples prefer male breadwinners and females doing home production. Then, gender role bias discourages females from working and males from doing more housework, and opportunity cost effects are dominated by the pressure to comply with prescriptive gender roles as female's relative wages increase.

Figure 1: Intra-household time shares and wage shares

(a) Labor (b) Home production



Note: Mexican Family Life Survey (2002-2009). British Household Panel Survey (1994-2004). The sample consists of nuclear households with positive time allocated to each activity, including households with missing wage information. Wage is imputed if missing.

To further explore the relationship between time shares and wage shares, I relax the linearity assumption from (1) and run the following semiparametric panel regression for each country

$$y_{it} = f(x_{it}) + \beta' Z_{it} + f_i + f_t + e_{it} \tag{2}$$

where $f(\cdot)$ is some function. The main interest is to evaluate the nonparametric fits of wage shares, $f(x_{it})$, for each time use, which is plotted in Figure 2.

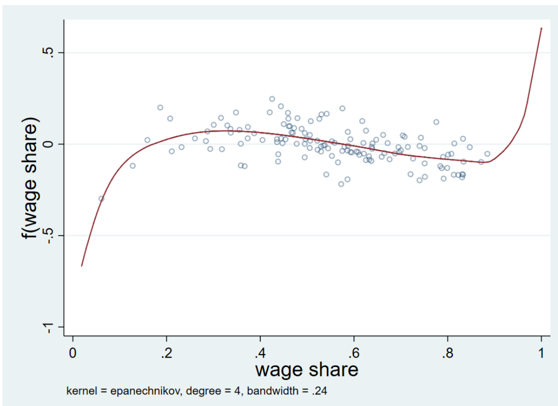
Figure 2 shows that there are nonlinearities between female wage shares and labor and home production shares in Mexico and the U.K., where the nonlinearity is most stark with home production shares in Mexico. Figure 2b shows that home production shares are negatively correlated with wage shares if wage shares are below 0.4 and positively correlated if wage shares are above 0.4.[18] Furthermore, it is around a similar threshold that there is a kink in the correlation between labor shares and wage shares, but in the opposite direction as showns in Figure 2a. Although the patterns in the U.K. are not as obvious as those in Mexico, Figure 2d suggests home production shares and

[18]The nonparametric fits in the tails are weak due to small data points.

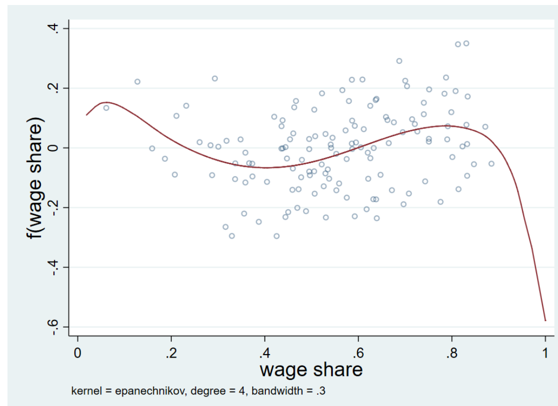
wage shares are not correlated when wage shares are above 0.4, and they are positively correlated only when wage shares are above 0.4, which is another form of nonlinearity. These nonlinearities indicate that, once the relative female wage is above a threshold, there is a counteracting force, potentially gender role bias, that deters females from increasing their labor but rather increases their home production even when their opportunity cost is higher.

Figure 2: Nonparametric fit of wage shares on time shares

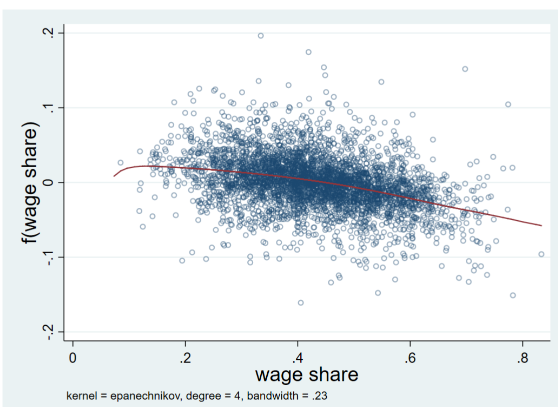
(a) Mexico: Labor



(b) Mexico: Home production



(c) U.K.: Labor



(d) U.K.: Home production

Note: Mexican Family Life Survey (2002-2009). British Household Panel Survey (1994-2004). The sample consists of nuclear households with positive time allocated to each activity, including households with missing wage information. Wage is imputed if missing.

To find thresholds at which correlations between a female's time share and wage share change for Mexico and the U.K., I use a fixed-effect panel threshold model from Hansen (1999) and estimate the following piecewise linear equation for each assumed threshold $\bar{x}$ in a given country

$$y_{it} = \beta_0 + \beta_1(1 - D_{it})x_{it} + \beta_2 D_{it}x_{it} + D_{it} + \beta' Z_{it} + f_i + f_t + e_{it} \tag{3}$$

where D_{it} is a binary variable that takes the value one if $x_{it} > \bar{x}$. After estimating (3) for a number of assumed thresholds, ranging over [0.5 0.95] in increments of 0.01, I choose a threshold that generates minimum SSE for each country. I find that a threshold value of females' wage shares is 0.56 for Mexico and 0.46 for the U.K. Both threshold values are near 0.5 which corroborates the conjecture that social norms against female breadwinners influences how couples allocate time.

In addition to cross-country variations, I explore if gender role bias plays a role when couples make time allocation decisions within one country, the U.K., to control for contextual differences across countries. To do this, I first build a Gender Role Bias Index (GBI) for the U.K. households to measure household-level gender role biased-ness using responses to survey questions about gender roles and Principal Component Analysis following Goussé et al. (2017) who uses the same data but a different set of questions. Each question asks, on a scale from 1 to 5, whether the person agrees with a statement regarding gender roles, with 1 meaning strongly agree and 5 meaning strongly disagree. Table 1 lists the survey questions and their factor loadings used to construct the index. The constructed GBI is high if the couple exhibits strong gender role bias and it ranges from 0 to 6.

Table 1: Gender Bias Index

Survey questions	Loading
Pre-school child suffers if mother works	-0.307
Family suffers if mother works full-time	-0.328
Woman and family happier if she works	0.229
Husband and wife should both contribute	0.176
Full-time job makes woman independent	0.155
Husband should earn, wife stay at home	-0.269
Children need father as much as mother	-0.050

Equipped with the GBI, I explore if couples' time allocations are heterogeneous in bias by analyzing the relationship between wage shares and earnings shares. Since gender role bias is related to relative earnings within a couple, I expect female's earning shares to be strongly impacted by GBI. To test this conjecture, I run the following panel regression

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 x_{it} GBI_i + \beta' Z_{it} + f_i + f_t + e_{it} \tag{4}$$

where y_{it} is female labor earning shares, x_{it} is female wage shares, and the main coefficients of interests are β_1 and β_2. For robustness, I also include male's wage and GBI interacted with male's wage as additional controls. The results are reported in Table 2. I find that when females wage share increases, her earnings share increases. However, the correlations are weaker for more biased, high GBI households. This is what we expect given the conjecture that gender role bias deters females from earning more: females in more biased households are discouraged from earning more as compared to females in less biased households.

To summarize, the empirical patterns show that there is a positive correlation between female wage shares and female home production shares and a negative correlation between female wage shares and labor shares persistently across countries and that these patterns cannot be explained by

Table 2: Wage shares and labor earning shares by GBI

	Labor earning share	
	(1)	(2)
Wage share	0.9368***	0.8613***
	(0.0333)	(0.0392)
Wage share × GBI	-0.0383***	-0.0293*
	(0.0107)	(0.0123)
Male wage		-0.0033***
		(0.0010)
Male wage × GBI		0.0001
		(0.0003)
Controls	Yes	Yes
Fixed effects	Yes	Yes
N	6259	6259

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

any observable characteristics and are inconsistent with predictions of standard collective household models. So, I propose gender role bias as another channel through which working couples' time allocations can be rationalized. If female's relative wage increases, push-back from the bias also increases to offset her incentive to work more. The observed patterns support this argument because the puzzling correlations are more substantial in Mexico than in the U.K. where gender role bias is known to be stronger. Moreover, I find that even within a country, couples' decisions are impacted by how biased a given household is, which supports the argument that gender role bias matters when it comes to understanding how couples behave. Motivated by the empirical analyses, I build a structural household model with gender role bias in the next section to use it to quantify the distributional effects of fiscal policies that change couples' wage shares.

4 Structural household decision model

Consider a household k at time t with two decision-makers, a female and a male $i \in \{f, m\}$, who enjoy private consumption, leisure, and public consumption of domestically produced good. Each individual is endowed with time, normalized to 1, that can be spent on leisure l_{tki}, labor q_{tki}, and home production h_{tki}, and earns hourly wage of w_{tki} if he or she works. An individual's time-invariant utility function is $U_{ki}(c_{tki}, l_{tki}, H_{tk})$ where c_{tki} denotes private consumption of the market good whose price is normalized to 1, and H_{tk} denotes home produced public good.

The technology for the home produced goods is $g(h_{tkf}, h_{tkm})$, which takes female's and male's time, h_{tkf}, h_{tkm}, as inputs.[19] Home production includes childcare and other house chores such as washing dishes and doing laundry, and the output can be thought as the sub-utility that individuals

[19]We do observe intermediate goods expenditure such as expenditures on detergents, soap, and children's clothes in the data. So we can include intermediate goods as another input for home production.

enjoy from children's well-being or a clean house.

Furthermore, households are gender role biased towards having males work and females do home production. As a result, a household suffers disutility if females' labor earnings increase as compared to males'.[20] In the model, disutility is represented by a function $d_k(w_{tkf}q_{tkf}, w_{tkm}q_{tkm}) \leq 0$, which is an increasing function of female's labor earnings: $\frac{\partial d_k}{\partial(w_{tkf}q_{tkf})} \leq 0$, $\frac{\partial d_k}{\partial(w_{tkm}q_{tkm})} \geq 0$.

Finally, given the wage offers and home production technology, a household k solves the following static problem at every t:

$$
\begin{aligned}
\underset{\substack{c_{tkf},l_{tkf},h_{tkf},q_{tkf} \\ c_{tkm},l_{tkm},h_{tkm},q_{tkm}}}{\text{Max}} \quad & \mu_{tk}U_{kf}(c_{tkf}, l_{tkf}, H_{tk}) + (1-\mu_{tk})U_{km}(c_{tkm}, l_{tkm}, H_{tk}) \\
& + d_k(w_{tkf}q_{tkf}, w_{tkm}q_{tkm}) && (5) \\
\text{s.t.} \quad & c_{tkf} + c_{tkm} = w_{tkf}q_{tkf} + w_{tkm}q_{tkm} && (6) \\
& l_{tkf} + q_{tkf} + h_{tkf} = 1 && (7) \\
& l_{tkm} + q_{tkm} + h_{tkm} = 1 && (8) \\
& H_{tk} = g(h_{tkf}, h_{tkm}) && (9) \\
& c_{tki}, l_{tki}, q_{tki}, h_{tki} \geq 0 \quad \text{for} \quad i \in \{f, m\} && (10)
\end{aligned}
$$

where μ_{tk} is the Pareto weight on female's utility, and $1-\mu_{tk}$ is the Pareto weight on male's utility. If disutility from bias is absent, the above household optimization problem follows the collective household model framework from papers including Chiappori (1988) and Blundell et al. (2005). I assume, following the collective household literature, that the Pareto weight depends on the age difference and education level difference between the members of the couple. Furthermore, I allow the Pareto weights to change across time.

Then, we can derive a model implication on how gender role bias affects couples' decisions. For each household k at a given time t, let $\lambda_{tk1}, \lambda_{tk2}, \lambda_{tk3}, \lambda_{tk4}$ be Lagrangian multipliers for the budget constraint, time constraint for female and male respectively, and home production technology constraint. Then, we can derive the following relationships from first order conditions

$$\lambda_{tk2} = MU_{l_{tkf}} = MU_{h_{tkf}} \tag{11}$$

$$\lambda_{tk3} = MU_{l_{tkm}} = MU_{h_{tkm}} \tag{12}$$

$$\frac{1}{w_{tkm}}\lambda_{tk3} = \frac{1}{w_{tkf}}\lambda_{tk2} - \frac{\partial d_k}{\partial(w_{tkf}q_{tkf})}w_{tkf} + \frac{\partial d_k}{\partial(w_{tkm}q_{tkm})}w_{tkm} \tag{13}$$

where MU_x is the couple's marginal utility from x. Using these equations, we can derive the key model implication of gender role bias: that a household's marginal rate of substitution between male's and female's time (in leisure or home production) depends on the magnitude of gender role

[20]Both genders suffer if female's labor earning increase following Akerlof and Kranton (2000)'s argument that a sense of self, or identity, is associated with how people in different social categories should behave, and that "violating the prescriptions evokes anxiety and discomfort in oneself and in others".

bias. To be more specific, we see that the following holds when we plug (11) and (12) into (13):

$$MRS_{l_{tk}} \equiv \frac{MU_{l_m}}{MU_{l_{tkf}}} \geq \frac{w_m}{w_{tkf}} \tag{14}$$

$$MRS_{h_{tk}} \equiv \frac{MU_{h_m}}{MU_{h_{tkf}}} \geq \frac{w_m}{w_{tkf}}. \tag{15}$$

The inequalities imply that in the presence of gender role bias, the households consume more female housework (and leisure) compared to the case where there is no bias. As a result, female's relative home production and leisure is higher and her relative labor is lower than when bias does not exist ($d_k = 0$).

5 Empirical implementation

5.1 Model specifications

In this paper, I assume Pareto weights are exogenous and random while individual's utility is heterogeneous and time invariant. Since I jointly identify Pareto weights and individual's preference, this is equivalent to assuming individual's utility is heterogeneous and time varying while Pareto weights are fixed at any value in (0,1) for all households.[21] Therefore, for the purpose of the estimation, I will assume Pareto weights are fixed at 0.5 for all households and individual's utility is time-varying as follows

$$U_{tki}(c_{tki}, l_{tki}, H_{tk}) = \alpha_{tki1} log(c_{tki}) + \alpha_{tki2} log(l_{tki}) + \alpha_{tki3} log(H_{tk}) \tag{16}$$

where $0 < \alpha_{tkij} < 1, j \in \{1, 2, 3\}$ and $\sum_{j=1}^{3} \alpha_{tkij} = 1$ for $i \in \{f, m\}$ at every t.

I assure α's lie between 0 and 1, and sum to 1 by following the normalization method from recent literature including Lise and Yamada (2018) and Verriest (2019). Specifically, each household draws at every time t a random 4-dimensional vector from a multivariate normal distribution $N(\beta, \Sigma)$ where β is a 4×1 vector and Σ is a 4×4 matrix where covariances are allowed to be nonzero. Then, given each houshold's random draw $\beta_{tk} = (\beta_{tkf2}, \beta_{tkf3}, \beta_{tkm2}, \beta_{tkm3})$, α's are constructed such that the following holds for each individual $i \in \{f, m\}$ in the household

$$\alpha_{tki1} = \frac{1}{1 + exp(\beta_{tki2}) + exp(\beta_{tki3})} \tag{17}$$

$$\alpha_{tki2} = \frac{exp(\beta_{tki2})}{1 + exp(\beta_{tki2}) + exp(\beta_{tki3})} \tag{18}$$

$$\alpha_{tki3} = \frac{exp(\beta_{tki3})}{1 + exp(\beta_{tki2}) + exp(\beta_{tki3})}. \tag{19}$$

[21] In Appendix C, I show parametric assumptions and identification strategies where Pareto weights and preference parameters can be separately identified.

Furthermore, disutility from gender norm bias is

$$d_k(w_{tkf}q_{tkf}, w_{tkm}q_{tkm}) = -\left(\frac{w_{tkf}q_{tkf}}{w_{tkf}q_{tkf} + w_{tkm}q_{tkm}} - \delta_k\right)^2 \mathbb{I}\left(\frac{w_{tkf}q_{tkf}}{w_{tkf}q_{tkf} + w_{tkm}q_{tkm}} > \delta_k\right) \quad (20)$$

where $\mathbb{I}$ is an indicator function. Under this specification, it is only when female's labor income share is above a threshold, $\delta_k \in [0, 1]$, that bias generates disutility. When it does, the magnitude of disutility is determined by the gap between female's labor income share and the threshold. If $\delta_k = 0.5$, it implies that disutility from gender role bias kicks in once females are the breadwinners. Having a threshold so that disutility from gender role bias is nonlinear is consistent with the semi-parametric analyses results in 3 where we observe a structural break in the relationships between a female's share of time and her share of wages around a threshold in Mexico and the U.K.

Furthermore, the threshold parameter δ_k depends on how biased a household is as follows

$$\delta_k = \frac{exp(\delta_0 + \delta_1 GBI_k + u_k)}{1 + exp(\delta_0 + \delta_1 GBI_k + u_k)} \quad (21)$$

where GBI_k is the Gender Bias Index constructed in section 3 rescaled to be between 0 and 1, which is higher for more biased households, and u_k is a random variable, independent of observables and drawn from the standard normal distribution. I expect $\delta_1 < 0$ so that the threshold is lower for more biased households. Since GBI_k is available for the U.K. households only, I estimate the model only using the U.K. data.

Finally, the home production technology follows a Constant Elasticity of Substitution function

$$g(h_{tkf}, h_{tkm}) = [s(h_{tkf})^\epsilon + (1 - s)(h_{tkm})^\epsilon]^{\frac{1}{\epsilon}} \quad (22)$$

where s is the weight on female's time, and $\frac{1}{1-\epsilon} > 0$ is the elasticity of substitution between two inputs. Time inputs are complements if $\epsilon < 0$, and substitutes if $0 < \epsilon < 1$. Under the parametric specifications, the model is estimated through the Simulated Method of Moments.

5.2 Identification strategy and estimation

The identification strategy relies on households who are choosing interior solutions (couples who allocate positive time on both gender's leisure, labor, and home production) across time, or "interior" households. So in this section, I focus on decisions of interior households to layout the identification and estimation strategies.

To identify the home production technology parameters (s, ϵ), I first use the condition that the marginal rate of substitution between female's and male's in leisure equals to that in home production, $MRS_l = MRS_h$, which can be derived from (11) and (12). Under the parametric specifications (16) and (22), this implies the following holds

$$\frac{\alpha_{tkf2}}{\alpha_{tkm2}} \frac{l_{tkm}}{l_{tkf}} = \left(\frac{h_{tkf}}{h_{tkm}}\right)^{\epsilon - 1} \frac{s}{1 - s} \quad (23)$$

which I can rewrite as follows

$$\ln\left(\frac{l_{tkm}}{l_{tkf}}\right) = \ln\left(\frac{s}{1-s}\right) + (1-\epsilon)\ln\left(\frac{h_{tkm}}{h_{tkf}}\right) - \ln\left(\frac{\alpha_{tkf2}}{\alpha_{tkm2}}\right). \tag{24}$$

Pooling observations across time and households, we can identify (s, ϵ) and the distribution of $\frac{\alpha_{tkf2}}{\alpha_{tkm2}}$ using variations in relative leisure and relative home production time and equation (24). Taking the identification strategy to estimate parameters (s, ϵ), I use indirect inference and target log-linear regression coffecients of (24) as moments to match. Additionally, I take means of relative leisure and home production time as additional moments to match.

Once I know the home production technology parameters, I can identify the gender role bias parameters (δ_0, δ_1) by exploiting the model implication that marginal rate of substitution in time between genders is equal to or above wage ratios as mentioned in section 4. Specifically, I can expand the model implication (15) as follows

$$MRS_{h_{tk}} \equiv \frac{MU_{h_{tkm}}}{MU_{h_{tkf}}} \begin{cases} = \frac{w_{tkm}}{w_{tkf}} & \text{if } D_{tk} = 0 \\ > \frac{w_{tkm}}{w_{tkf}} & \text{if } D_{tk} = 1 \end{cases} \tag{25}$$

where

$$D_{tk} \equiv \mathbb{I}\left(\frac{w_{tkf}q_{tkf}}{w_{tkf}q_{tkf} + w_{tkm}q_{tkm}} > \delta_k\right). \tag{26}$$

Using the parametric assumptions and above model implication, I can derive the following relationship between relative home production time and relative wages

$$\left(\frac{h_{tkm}}{h_{tkf}}\right)^{\epsilon-1} \frac{1-s}{s} \begin{cases} = \frac{w_{tkm}}{w_{tkf}} & \text{if } D_{tk} = 0 \\ > \frac{w_{tkm}}{w_{tkf}} & \text{if } D_{tk} = 1. \end{cases} \tag{27}$$

Since everything is known in (27), I can calculate the probability that $D_{tk} = 1$ for each δ_k, or for households with the same GBI_k levels. Then, I can use the probability distribution to identify the gender role bias parameters (δ_0, δ_1) from (20). Taking the identification strategy, I use $Pr(D_{tk} = 1|GBI_k)$ as a moment to target to estimate gender role bias parameters.

Finally, given that I know the gender role bias parameters and home production technology parameters, the only unknown parameters are preference parameters α_{tki}'s. To identify α_{tki}'s, I can exploit variations in levels of wages and of leisure or home production time. Related moments that I target for estimation include mean levels and standard deviations of leisure and home production time for each gender, and correlations in time across gender as well as within gender, conditional on GBI_k levels.

6 Estimation results

The number of moments used in Simulated Method of Moments is reported in Table 3, and a full list of moments and corresponding data moments, simulated moments, and weights are reported in Table 4.

The estimates for all parameters are reported in Table 5. For interpretability, I report means and standard deviations of preference parameters. On average, both females and males value leisure most over consumption and home production. However, females value home production more than males. In the model, home production includes childcare so we can interpret output of home production to include utility coming from children's well-being. In this case, the estimates are consistent with the literature that finds female empowerment improves children's welfare because females value children's well-being more than males (Duflo, 2003).

The average threshold above which gender role bias triggers disutility is 0.447, which is close to the idea that there is bias against female breadwinners (Bertrand et al., 2015). Furthermore, $\delta_1 < 0$ implies that the threshold is lower for more biased households, or higher-GBI households, which is what we expect based on the model setting and the threshold parameter interpretation: as more biased households have stronger bias against working females, disutility is triggered when females earn little relative than males.

Finally, home production technology is such that females are more productive relative to males. The estimate of ϵ indicates that the elasticity of substitution between two time inputs $(1/(1-\epsilon))$ is close to one, meaning two time inputs are weakly substitutes and the home production technology is close to Cobb Douglas. These results are similar to Cherchye et al. (2012) where they find females are more productive than males, and on average, the elasticity of substitution for childcare is about 1, and the elasticity of substitution for house chores is slightly higher, around 1.18.

Table 3: Number of Moments

Obj. Value	Number of moments	Moments with pos. var.
2025.77	45	45

Table 4: Data vs. Simulated Moments

	Data	Sim	Weight	Obj. %
$E(h_f/h_m \mid GBI < 3, \text{working couple})$	2.543	2.606	10.82	0.00
$E(h_f/h_m \mid 3 \leq GBI < 5, \text{working couple})$	2.845	2.601	3.30	0.01
$E(h_f/h_m \mid GBI \geq 5, \text{working couple})$	2.175	2.510	122.27	0.68
$E(l_f/l_m \mid GBI < 3, \text{working couple})$	1.017	1.050	11773.07	0.65
$E(l_f/l_m \mid 3 \leq GBI < 5, \text{working couple})$	1.019	1.029	25707.86	0.12
$E(l_f/l_m \mid GBI \geq 5, \text{working couple})$	1.011	1.016	30454.82	0.05
$corr(l_f, h_f \mid \text{working couple})$	-0.171	-0.287	726.69	0.48
$corr(l_m, h_m \mid \text{working couple})$	-0.278	-0.067	316.92	0.70
$corr(l_f, l_m \mid \text{working couple})$	0.511	-0.067	356.72	5.88
$corr(h_f, h_m \mid \text{working couple})$	0.516	0.584	677.08	0.16
$corr(l_f, h_m \mid \text{working couple})$	-0.147	-0.070	546.11	0.16
$corr(h_f, l_m \mid \text{working couple})$	-0.352	-0.407	596.13	0.09
$\widehat{\beta_0}(y = hp_{share}, x = l_{share}, GBI < 0.3, \text{working couple})$	0.028	-0.001	1354.38	0.06
$\widehat{\beta_1}(y = hp_{share}, x = l_{share}, GBI < 0.3, \text{working couple})$	0.053	0.047	597.93	0.00
$\widehat{\beta_0}(y = hp_{share}, x = l_{share}, 0.3 \leq GBI < 0.5, \text{working couple})$	0.001	-0.001	9547.43	0.00
$\widehat{\beta_1}(y = hp_{share}, x = l_{share}, 0.3 \leq GBI < 0.5, \text{working couple})$	0.024	0.024	7195.91	0.00
$\widehat{\beta_0}(y = hp_{share}, x = l_{share}, GBI \geq 0.5, \text{working couple})$	0.004	0.022	14674.61	0.25
$\widehat{\beta_1}(y = hp_{share}, x = l_{share}, GBI \geq 0.5, \text{working couple})$	0.018	0.035	8201.81	0.12
$Pr(D = 1 \mid GBI < 3, \text{working couple})$	0.260	0.335	103.47	0.03
$Pr(D = 1 \mid 3 \leq GBI < 5, \text{working couple})$	0.195	0.252	1067.01	0.17
$Pr(D = 1 \mid GBI \geq 5, \text{working couple})$	0.270	0.314	759.03	0.07
$E(l_f \mid GBI < 0.3, \text{working couple})$	0.631	0.667	5572.95	0.36
$E(l_f \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.627	0.656	90314.89	3.65
$E(l_f \mid GBI \geq 0.5, \text{working couple})$	0.621	0.652	100331.20	4.63
$E(l_m \mid GBI < 0.3, \text{working couple})$	0.623	0.637	4319.23	0.04
$E(l_m \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.618	0.639	63233.10	1.39
$E(l_m \mid GBI \geq 0.5, \text{working couple})$	0.617	0.644	86177.06	3.18
$E(h_f \mid GBI < 0.3, \text{working couple})$	0.185	0.280	5838.57	2.56
$E(h_f \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.170	0.281	34781.38	21.31
$E(h_f \mid GBI \geq 0.5, \text{working couple})$	0.166	0.276	35028.98	20.97
$E(h_m \mid GBI < 0.3, \text{working couple})$	0.087	0.116	13417.02	0.55
$E(h_m \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.084	0.117	95866.24	5.06
$E(h_m \mid GBI \geq 0.5, \text{working couple})$	0.085	0.118	156388.82	8.35
$St.Dev(l_f \mid GBI < 0.3, \text{working couple})$	0.061	0.054	4231.75	0.01
$St.Dev(l_f \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.038	0.060	202331.48	5.09
$St.Dev(l_f \mid GBI \geq 0.5, \text{working couple})$	0.037	0.063	172825.41	5.50
$St.Dev(l_m \mid GBI < 0.3, \text{working couple})$	0.066	0.035	3181.05	0.16
$St.Dev(l_m \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.048	0.034	161660.79	1.51
$St.Dev(l_m \mid GBI \geq 0.5, \text{working couple})$	0.042	0.037	189286.97	0.24
$St.Dev(h_f \mid GBI < 0.3, \text{working couple})$	0.061	0.045	54312.67	0.67
$St.Dev(h_f \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.063	0.047	129184.14	1.51
$St.Dev(h_f \mid GBI \geq 0.5, \text{working couple})$	0.067	0.048	118053.50	2.12
$St.Dev(h_m \mid GBI < 0.3, \text{working couple})$	0.035	0.041	50983.67	0.10
$St.Dev(h_m \mid 0.3 \leq GBI < 0.5, \text{working couple})$	0.033	0.039	245712.72	0.42
$St.Dev(h_m \mid GBI \geq 0.5, \text{working couple})$	0.034	0.041	343617.58	0.93

Table 5: Parameter estimates

(a) Female's preferences	Mean	Std.
Consumption (α_f^1)	0.206	0.073
Leisure (α_f^2)	0.585	0.034
Home production (α_f^3)	0.209	0.080
(b) Male's preferences	**Mean**	**Std.**
Consumption (α_f^1)	0.156	0.026
Leisure (α_f^2)	0.689	0.051
Home production (α_f^3)	0.155	0.026
(c) Correlations		
Correlation of α_f^2 and α_f^3	-0.407	
Correlation of α_f^2 and α_m^2	0.580	
Correlation of α_f^2 and α_m^3	-0.577	
Correlation of α_f^3 and α_m^2	0.018	
Correlation of α_f^3 and α_m^3	-0.018	
Correlation of α_m^2 and α_m^3	-1.000	
(d) Gender role bias		
Mean threshold ($E(\delta)$)	0.447	
Intercept (δ_0)	0.492	
GBI (δ_1)	-1.456	
(e) Home production technology		
Weight on Female's time (s)	0.663	
Elasticity (ϵ)	-0.004	

Notes: Standard Errors are computed using a cluster bootstrap sampling each household with replacement (Work in process).

7 Policy implications of gender role bias

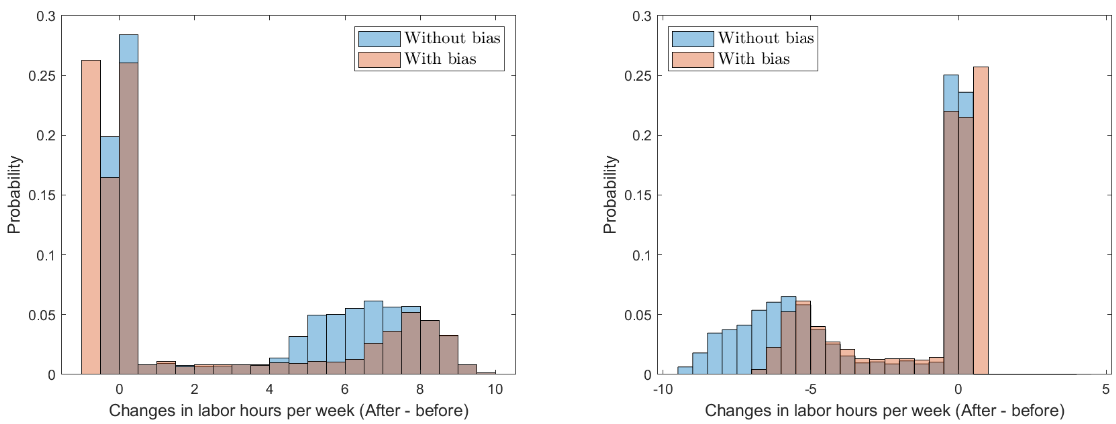
Given the estimated model primitives, I compare predicted distributional effects of a policy from two models to evaluate the importance of acknowledging gender role bias. I use the model with gender role bias as the baseline, and compare its policy predictions with the counterfactual model where gender role bias is ignored, or $\delta_k = 1$ for all households. In particular, I focus on fiscal policies that increase females' effective wages with the goal of reducing gender differences in labor hours. One example is changing a joint tax filing system to an individual filing. Under the joint system, secondary earners face higher marginal tax rates than primary earners because tax rates increase as household income levels increase. However, under the individual filing system, this is no longer the case. As a result, the systematic shift decreases secondary earners' marginal tax rates and increases their effective wages. This is expected to disproportionately increase females' effective wages relative to males' because most working females are secondary earners.[22] Another example is gender-based taxation where distinct tax rates are imposed depending on gender. For example, Alesina et al. (2011) argues gender-based taxation in which tax rates on labor income is lower for women than for men has distributional benefits when intrahousehold redistribution is explicitly taken into account.

As a stylized analysis that mimics these fiscal policies, I increase females' wages by 10 percent for all households and predict its effects on couples' time allocations through the lens of each model. This is analogous to the gender-based taxation where labor tax rates for females across all income levels are lowered by 10 percentage while labor tax rates for males are unchanged.

Figure 3 plots the distributions of labor hours change for each gender when females' wages increase, predicted by the counterfactual model ignoring bias and the baseline model acknowledging bias, respectively. I find that both models predict female labor hours would increase and male labor hours would decrease on average, but to a larger degree in the counterfactual model case.

Figure 3: Distribution of labor hours change

(a) Female (b) Male



Note: "Without bias" is the prediction of the counterfactual model where $\delta = 1$ for all households. "With bias" is the prediction of the baseline model.

Table 6 reports aggregate mean changes of couples' labor, home production, and earnings, in response to the females' wage increase. Again, both models predict the same qualitative results but the magnitude of predicted changes in time allocation and earnings is larger in the counterfactual model. For instance, the counterfactual model predicts female labor hours would increase by around 5 percentage point more than the baseline model. To recapitulate, both Figure 3 and Table 6 suggest that ignoring bias to predict policy effects can lead to overestimated predictions.

[22] Countries that adapt a joint tax filing system includes, but not limited to, the U.S., France, Germany, an Italy. Note that the tax system in the U.K. is an individual filing system. So the systematic gender differences in marginal tax rates from the tax filing system is minimal in the U.K.

Table 6: Comparing expected policy impacts: changes in mean

Changes (After/Before) in		**Mean**	
		Without bias	**With bias**
Home production	Female	0.979	0.989
	Male	1.023	1.009
Labor	Female	1.219	1.170
	Male	0.925	0.975
Earning	Female	1.298	1.246
	Male	0.943	0.977
Total household earning		1.028	1.021

Notes: "Without bias" is the prediction of counterfactual model where $\delta = 1$ for all households. "With bias" is the prediction of the baseline model.

8 Conclusion

This paper examines how gender role bias affects time allocation decisions within a household. Specifically, it focuses on the way such bias influences working couples' response to relative wage changes, and it highlights the importance of taking gender role bias into account to accurately predict policy effects on labor market outcomes.

Using panel survey data from two countries, I show that females' relative labor hours decrease even when their relative wages increase; at the same time, females' relative home production hours increase as their relative wages increase. The relationship is even stronger in a country that has been shown to have a higher degree of gender bias. Furthermore, to add support for the conjecture, I focus on households in the U.K. to evaluate if couples' decisions vary by how biased households are. Constructing an index based on survey questions to measure each household's degree of bias, I find that if couples are more biased, female's relative earnings are less elastic to female's relative wages. These patterns corroborate a conjecture that gender role bias deters females from allocating more time in labor even when their relative wages increase.

To study the quantitative implication of gender role bias when making policy predictions, I build a structural household model with gender role bias which rationalizes the observed patterns. In particular, the bias is modelled such that there is disutility for couples once female's labor earnings is higher than a threshold. After estimating the model with working couples in the U.K., I find that couples face disutility as females start earning more than their husbands, as is expected from gender role bias. Given the estimated primitives of the model, I evaluate a policy that increases females' effective wages to decrease gender gaps in labor supply. I do this using two models, one ignoring gender role bias and the other incorporating it. Comparing predictions of the two models, I show that the policy effects are overestimated if the bias is ignored.

There are other types of policies other than fiscal policies that changes couples' behavior and their division of labor. For example, family policies, such as public childcare service provisions, are interventions that can change couples' behavior. To shed more light on the welfare effects of children and related family policies, a potential extension of this paper would be to endogenize fertility choices while allowing for service or goods to be purchased so that they can substitute couples' time in home production.

Furthermore, because wages are exogeneous, we can interpret the policy analyses in this paper to be short-run analyses. For long-run policy implications, we can extend the model to be dynamic with human capital accumulation where wages depend on experience.

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Appendices

A Details on time allocation data

Here I lay out the details of time use and wage data that are exploited.

Mexico: For labor time, I use answers to following questions about main jobs:[23] "Normally, how many hours per week do you work?"[24] "From Monday through Sunday of last week, how much time did you spend going to work and coming back home?" For home production time and leisure time (except sleeping hours), we use answers to questions about length of time spent in each category of activity in the following manner: "From Monday through Sunday of last week, how many hours did you [activity category]?" For sleeping time, we use answers to the following question: "How many hours do you sleep daily?". The answer is multiplied by 7 to be weekly data.

For hourly wages, I use answers to following questions: "How much did you earn last month, since (SAY THE DATE OF A MONTH AGO) until today, for working as [main job description]?" " How much did you earn the last twelve months, since (SAY THE DATE OF 12 MONTHS AGO) until today, for working as [main job description]?" The questions ask for the detailed amount but if it is not known, total amount is asked. Total amount includes wage/salary (after tax), piecework, commissions and tips, extra hours, meals, housing, transportation, medical benefits, and others. If answers for monthly wage and yearly wage are different, we take the mean of two answers. Yearly answers are transformed to weekly by dividing answers by (12*30)/7. Monthly answers are transformed to weekly by dividing the answers by 30/7. Hourly wage is computed by using reported total amount earned, transformed to weekly, and divided by weekly labor time.

U.K.: As mentioned in the main body, I use calibrated time use data for U.K. provided by BHPS.

For wage, BHPS has a dataset that provides estimated real wage information. However, I calculate hourly wages using following information. I take gross monthly pay, gross pay at latest payment whose covering period is reported, or usual pay from payslip whose covering period is reported as measures of income. Then, I collect the reported covering period of payments and calibrated number of hours worked per week to calculate hours spent working. Then, I divide the income by hours spent working to derive hourly wages.

B Details on selection bias correction for wage imputations

In MxFLS, wage information is available if an individual is an employee and reports his/her income. Therefore, wage information is unobserved for following groups of individuals.

1. Employed but not reported income.

[23] Main job is defined as the job where an individual earn the majority of his/her income.

[24] There is another question asking how many hours an individual worked last week. Answers for normal work time and last-week work time are same for most answers while about 15 % of answers were different in MxFLS-3. Data patterns still persist when I use hours worked last week instead of hours worked on usual week.

2. Unemployed or working for no-pay: I treat those who are working for no pay or unemployed as one group because both types do not contribute to household's financial conditions.
3. Self-employed or entrepreneurs.

Because there is selection over multiple choices, the first stage selection is specified as a multinomial logit model to implement a selection bias correction method rather than as a univariate probit as in the Heckman model. Explanatory variables that are included in both first and second stages are gender, education levels, age, and gender interacted with education levels and age. Selection variables that satisfy the exclusion restriction include a dummy for the existence of children taking value 1 if there are children, number of females and males in the household, spouse's age and education level, and a dummy for spouse's employment sector taking value 1 if the spouse works in the formal sector. An individual is employed in a formal sector if the insurance is provided by his/her employer.

C Separately identifying Pareto weights and preference parameters

To separately identify Pareto weights and preference parameters, we assume an individual utility is time-invariant as follows

$$U_{ki}(c_{tki}, l_{tki}, H_{tk}) = \alpha_{ki1} log(c_{tki}) + \alpha_{ki2} log(l_{tki}) + \alpha_{ki3} log(H_{tk}) \tag{28}$$

where preference parameters are random across individual i and household k, and normalized such that $0 < \alpha_{kin} < 1, n \in \{1, 2, 3\}$ and $\sum_{n=1}^{3} \alpha_{kin} = 1$ for $i \in \{f, m\}$.

Pareto weight of each household k at time t depends on an error term ($e_{tk} \sim N(0, 1)$, i.i.d.) and weights are normalized to be between 0 and 1 such that

$$\mu_{tk} = \frac{exp(\mu_0 + \mu_1 e_{tk})}{1 + exp(\mu_0 + \mu_1 e_{tk})} \tag{29}$$

where μ_1 determines the variance of e_{tk}.

Having identified gender role bias threshold and home production technology parameters following the strategy explained in section 5, we can identify Pareto weights, μ_{tk}, using variations over time in leisure for each gender. The key identification assumption is that preference is time-invariant, while the Pareto weights are time-varying. Under the assumption, I argue the across time variations in an individual's leisure demand are due to changes in Pareto weights.

This is easy to see for households with $D_{tk} = 0$ where the ratios of leisure demand at t and $t + 1$

for each gender are

$$Male: \quad \frac{l_{t,km}}{l_{t+1,km}} = \frac{w_{t,kf}+w_{t,km}}{w_{t+1,kf}+w_{t+1,km}}\frac{w_{t+1,km}}{w_{t,km}}\frac{1-\mu_{t,k}}{1-\mu_{t+1,k}} \tag{30}$$

$$Female: \quad \underbrace{\frac{l_{t,kf}}{l_{t+1,kf}}}_{\substack{\text{leisure}\\ \text{ratio}}} = \underbrace{\frac{w_{t,kf}+w_{t,km}}{w_{t+1,kf}+w_{t+1,km}}}_{\substack{\text{Value of endowed time}\\ \text{ratio}}}\underbrace{\frac{w_{t+1,kf}}{w_{t,kf}}}_{\substack{\text{Wage}\\ \text{ratio}}}\underbrace{\frac{\mu_{t,k}}{\mu_{t+1,k}}}_{\substack{\text{Pareto weight}\\ \text{ratio}}}. \tag{31}$$

As we see from above, the leisure ratio (at t and $t+1$) depends on wages and Pareto weights, and we observe everything from the data except Pareto weights. Then, unexplained variations in leisure ratios can identify distribution of Pareto weights.

The logic is similar for households with $D_{tk}=1$ but less obvious. The key is to identify parameters governing leisure demand ($\mu_{tk}\alpha_{kf2}$, $(1-\mu_{tk})\alpha_{km2}$) at each time t and separate μ_{tk} from α's using across-time differences. To do so, recall that marginal rate of substitution between gender in leisure must equalt to that in home production. Under the parametric assumptions, it implies the following holds

$$\frac{\mu_{tk}\alpha_{kf2}}{(1-\mu_{tk})\alpha_{km2}}\frac{l_{km}}{l_{kf}} = \left(\frac{h_{kf}}{h_{km}}\right)^{\epsilon-1}\frac{s}{1-s} \tag{32}$$

where everything is observable or known except parameters of interest $(\mu_{tk}\alpha_{kf2}, (1-\mu_{tk})\alpha_{km2})$. Furthermore, I know from (13) that

$$(1-\mu_{tk})\alpha_{km2} = \frac{w_{tkm}l_{tkm}}{w_{tkf}l_{tkf}}\mu_{tk}\alpha_{kf2} + 2D_{tk}\left(\frac{w_{tkf}q_{tkf}}{w_{tkf}q_{tkf}+w_{tkm}q_{tkm}} - \delta_k\right)\frac{w_{tkm}l_{tkm}}{w_{tkf}q_{tkf}+w_m q_{tkm}} \tag{33}$$

must hold and again, everything is known or observable except $\mu_{tk}\alpha_{kf2}$ and $(1-\mu_{tk})\alpha_{km2}$. Using two functions, I can identify the pair $(\mu_{tk}\alpha_{kf2}, (1-\mu_{tk})\alpha_{km2})$ at each time t. Finally, through variations of the pairs across time, I can separate Pareto weights μ_{tk} from preference parameters $\alpha_{kf2}, \alpha_{km2}$ because I assume α's are fixed across time.

Finally, given we know gender role bias threshold, home production technology, and Pareto weights parameters, we can exploit variations in levels of wages and of leisure and home production time to identify α's.

D Tables

Table 7: Sample selection (Mexico)

	Number of households
Original sample	10732
Nuclear	5729
Demographics	5507
Time use	4718
Positive male labor, female housework	4258
Observations	3507

Source: Mexican Family Life Survey. This table reports the number of households after several selection criteria are applied. Nuclear excludes extended households where more than 1 female and 1 male adults are present in the household. Demographics excludes households where observables such as age, education, number of kids, total expenditure, and region are missing. Time use excludes households where time use is unobserved. Positive male labor, female housework excludes households if male is not working or if female spends zero time in home production. Finally, two years excludes households if a household is observed only once across waves. The final row reports the number of total observations aggregated across time given the number of selected sample households.

Table 8: Sample selection (UK)

	Number of households
Original sample	8180
Nuclear	8180
Demographics	6763
Time use	3705
Positive male labor, female housework	2715
Observations	9184

Source: British Household Panel Survey (BHPS, 1994-2004). The number of households after several selection criteria are reported in this table. Nuclear excludes extended households where more than 1 female and 1 male adults are present in the household. Demographics excludes households where observables such as age, education, number of kids, total expenditure, and region are missing. Time use excludes households where time use is unobserved. Positive malelabor, female housework excludes households if male is not working or if female spends zero time in home production. Finally, two years excludes households if a household is observed only once across waves. The final row reports the number of total observations aggregated across time given the number of selected sample households.

Table 9: Summary statistics of the selected sample (Mexico)

	Mean (Standard Deviation)		
	Female	Male	Household
Time use per week, Share of own time:			
Leisure (including sleep)	0.585	0.532	
	(0.16)	(0.11)	
Market work (including commute)	0.0688	0.399	
	(0.13)	(0.11)	
Home production (including childcare)	0.346	0.0687	
	(0.16)	(0.10)	
Other observables:			
Age	0.351	0.373	
	(0.12)	(0.12)	
Education (levels)	1.728	1.849	
	(1.02)	(1.06)	
Hourly wage (MXN)	3162.7	2234.0	
	(3049.81)	(2091.14)	
Average kids age			0.0534
			(0.04)
Number of kids			1.834
			(1.30)
I(rural)			0.415
			(0.49)
HH total expenditure (1000 MXN)			774.8
			(1089.46)

Source: Mexican Family Life Survey. Wage is imputed if missing. Total expenditure is aggregated from consumption data. Hours are time spent weekly rescaled so that total hours add up to 1. I(rural) = 1 if a household lives in rural area.

Table 10: Summary statistics of the selected sample (UK)

	Mean (Standard Deviation)		
	Female	Male	Household
Time use per week, Share of own time:			
Leisure (including sleep)	0.648	0.626	
	(0.07)	(0.06)	
Market work (including commute)	0.181	0.288	
	(0.10)	(0.07)	
Home production (including childcare)	0.171	0.0869	
	(0.06)	(0.03)	
Other observables:			
Age	41.07	43.08	
	(11.30)	(11.33)	
Education (levels)	5.434	5.680	
	(2.77)	(2.79)	
Hourly wage (GBP)	6.327	8.686	
	(3.14)	(3.97)	
Average kids age			2.717
			(3.95)
Number of kids			0.933
			(1.07)
HH total earnings			2833.6
			(1527.31)

Source: British Household Panel Survey (BHPS, 1994-2004). Wealth level includes nonlabor and labor earnings. Hours are time spent weekly rescaled so that total hours add up to 1.

Table 11: Number of households in corner solutions (Mexico)

	Number of observations
Female labor > 0, Male HP > 0	649
Female labor $= 0$, Male HP $= 0$	1105
Female labor $= 0$, Male HP > 0	1451
Female labor > 0, Male HP $= 0$	302
Total	3507

Source: Mexican Family Life Survey. Wage is imputed if missing. Hours are time spent weekly rescaled so that total hours add up to 1.

Table 12: Number of households in corner solutions (UK)

	Number of observations
Female labor $>$ 0, Male HP $>$ 0	7962
Female labor = 0, Male HP = 0	0
Female labor = 0, Male HP $>$ 0	1213
Female labor $>$ 0, Male HP = 0	0
Total	9184

Source: British Household Panel Survey (BHPS, 1994-2004). Hours are time spent weekly rescaled so that total hours add up to 1.

Table 13: Across-country gender biasedness

	Gender Social Norms Index		
	GSNI1	GSNI2	No bias
Mexico	87.7	51	12.3
UK	54.6	25.5	45.4
US	57.31	30.07	42.69

Source: Gender Social Norms Index from World Values Survey (2005-2014). GSNI is the percentage of people with at least one bias among seven indicators, GSNI2 is the percentage of people with at least two biases among seven indicators, and No Bias is the share of people with no bias.

Table 14: Regression result

	time share (f/(f + m))		
	(1)	(2)	(3)
	Home production	labor	leisure
Wage share (f/(f + m))	0.2526***	-0.4059***	0.0919***
	(0.0327)	(0.0232)	(0.0088)
UK × Wage share (f/(f + m))	-0.1796***	0.3023***	-0.0586***
	(0.0365)	(0.0260)	(0.0098)
Constant	0.7481***	0.4445***	0.4773***
	(0.0249)	(0.0177)	(0.0067)
Fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	7484	7484	7484

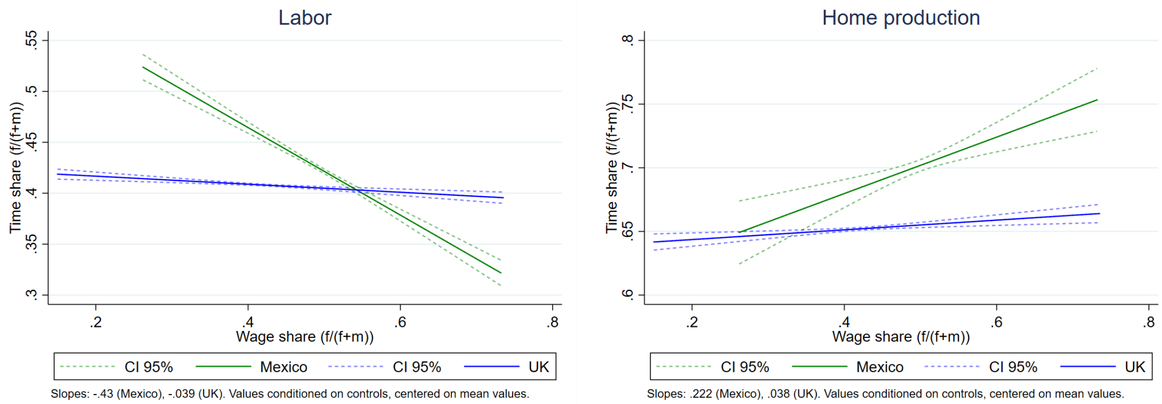
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Mexican Family Life Survey (2020-2009). British Household Panel Survey (1994-2004). The sample consists of nuclear households with positive time allocated to each activity, including households with missing wage information. Wage is imputed if missing.

E Graphs

Figure 4: Intra-household time shares and wage shares: households with wage information



Note:Mexican Family Life Survey (2002-2009). British Household Panel Survey (1994-2004). The sample consists of nuclear households with positive time allocated to each activity, excluding households with missing wage information.