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GENDER NORMS, TEMPORAL FLEXIBILITY, AND TALENT MISALLOCATION

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Abstract: To what extent do unequal gender roles in the household affect aggregate outputs when there is temporal inflexibility in the labor market? Following Goldin (2014) and Erosa et al. (2022)'s narrative of how disproportionate rewards to long hours create a source of distortion in the labor market, we explore the aggregate effects of gender differences exacerbated by nonlinear wage structures through a static model calibrated on US labor force data. Features of our model are similar to that of Erosa et al. (2022)'s with a few key differences that allow for a more nuanced analysis regarding time allocation and intra-household resource allocation. We discover that aggregate market output and women's market output increases by 6.14% and 10.96%, respectively, when we eliminate gender norms in the baseline counterfactual analysis. Our analysis additionally concludes that gender norms would lead to talent misallocation only if there are differences in the nonlinearity of wages across occupations.

Keywords: Gender, Time Allocation, Occupational Choice, Division of Labor, Wages, Misallocation

JEL: E24, J16, J22, J24, J31, J71, O47

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1 Introduction

Gender equality in the US labor market has taken great strides since the beginning of the last century in terms of participation, occupations, and earnings (Goldin, 2006). As innate talent within a group for a profession is unlikely to change over time, the convergence suggests that a large portion of the labor force was not optimally placed in the past, leading to talent misallocation in the economy. We use the term "misallocation" in line with literature that studies the aggregate consequences of resource allocation in an economy. While the majority of misallocation research focuses on the allocation of production factors and its implications for total factor productivity (TFP) growth (Hsieh and Klenow, 2009; Jones, 2013; Restuccia and Rogerson, 2017), talent misallocation at the micro level can also have important aggregate consequences for the economy. For example, Hsieh et al. (2019) have found that the reallocation of talent due to diminished barriers based on race and gender could explain up to 40% of aggregate growth in the US between 1960 and 2010.

Since the 1990s, there has been an evident slowdown in the gender convergence that persisted to this day, leaving, albeit a much narrower one, a gender gap that cannot be explained by observable characteristics. This implies that there remain possible economic gains for the economy that could be achieved by reallocating agents across occupations. Goldin (2014) and Erosa et al. (2022) offer a narrative that highlights the role of temporal flexibility in explaining this friction and its implications for the economy as a whole. For high-paying occupations, there is often a nonlinearity of wages in hours worked. Workers in these occupations are disproportionately rewarded for working long or particular hours and face substantial wage penalties for cutting back on hours. For the rest of the paper, we use the term "nonlinear" to describe occupations with disproportionate returns to hours worked.[1]

Although the US (and most of the developed world) has made great progress in gender equality, there is still a marked gender difference in time spent on housework such as housekeeping and childcare, which we will illustrate in detail in our data section. Because of the gender differences in housework responsibilities, women who work have a higher demand for temporal flexibility in the workplace. Thus, women are less likely to pursue "nonlinear occupations" where long or inflexible work hours are valued; and if they do enter these occupations, they are more vulnerable to pay cuts related to lower labor hours. This causes talent misallocation in the economy for women who would have excelled in these "nonlinear" occupations would be discouraged from pursuing these jobs, leading to less-than-optimal outputs for the aggregate economy.

[1] This term was first used by Goldin (2014) and later adopted by other related literature (e.g. Erosa et al. (2022); Jang and Yum (2022)).

To quantify the gender-related talent misallocation effects of nonlinear wage structures, we develop a model featuring occupational choice, time allocation (between market work, housework, and leisure), and nonlinear wage structures for our analysis. In our framework, each household consists of one man and one woman, and members of each household make occupational choices and allocate time between home production, market work, and leisure, to maximize their utility. Social norms regarding housework responsibilities are modeled as a disutility for households that increases with the wife's market hours. We adopt the nonlinear payment structure applied by Erosa et al. (2022) to reflect the difference in workplace flexibility in different occupations. Our occupational choice model is a modification of Roy (1951) with the addition of heterogeneous preferences for leisure and home production. The model is matched to empirical moments using US data for the period 2010-2019. We utilize the model to conduct counterfactual analyses to quantitatively determine the aggregate effects of the interaction between temporal inflexibility and gender norms.

Our counterfactual analysis finds results that are in line with Goldin (2014) and Erosa et al. (2022)'s perspective on the interaction between gender norms and nonlinear wage structures. We find that by removing social norms related to gender roles in the household, women's labor participation hours would increase by around 11% and aggregate market output would increase by around 6%. We also conduct analysis using different levels of nonlinearity and find that there would be no talent reallocation effects of removing social norms if there does not exist a difference in nonlinearity across occupations. A policy experiment involving subsidizing households with home production goods finds that such policies would have positive effects on aggregate market outputs, and a simple cost-benefit analysis of the policy experiment finds that benefits would outweigh the costs when the government subsidizes more than 30% of women's home hours.

The rest of the thesis proceeds as follows: In the next section, we review literature related to our study; Data and motivating facts are presented in Section 3; We specify our model in Section 4 and elaborate on our calibration strategy in Section 5; Quantitative results of our counterfactual and policy analyses are shown in Section 6; Finally, in Section 7, we conclude our findings.

2 Literature Review

2.1 An Overview of Gender Gaps in the Labor Market

Before the 1920s, female labor force participation in the US was low and largely linked to young, unmarried women from low-income families who mostly performed manual tasks in manufacturing occupations (Goldin, 1980, 2006). Despite a spike in female labor force participation due to the Second World War, studies have found little direct impact of the war on female labor force participation in the long run as most single, uneducated women who entered the labor force in that period only served as temporary substitutes to fill the void of male workers (Goldin, 1991; Rose, 2018; Schweitzer, 1980). However, shifts in labor market structures in the period coupled with exogenous societal changes like improved educational equality and technological advances[2] led to persistent effects for highly educated women. These women mostly entered white-collar occupations during wartime, and stayed in these jobs after the war as white-collar occupations continued to grow in size in the 1950s. Moreover, women have been found to be closer substitutes to men with high school degrees than those with lower skills (Acemoglu et al., 2004), which made female labor force participation more positively received in higher-skilled occupations than in those that require little education (e.g. manufacturing) (Goldin and Olivetti, 2013). The evolution of culture has also been found to have contributed to the increase in female labor force participation in the past century (Fernández and Fogli, 2009; Fernández, 2013).

Overall, the US labor market saw a sizeable increase in the participation of married women (or a diminished "marriage bar") and educated women for the better part of the last century (Goldin, 1988, 1991, 2006). The gender gap in earnings stayed mostly constant after World War II until around the 1970s,[3] which marked the beginning of a rapid gender convergence in earnings as women began to move out of "secondary earner" roles in the household to actively pursue their own careers (Goldin, 2006). The convergence took place despite increasingly unfavorable wage structures for low-skilled workers as women's observable characteristics rapidly caught up to that of men's in the period (Blau and Kahn, 1997).

However, the gender convergence in earnings stagnated in the 1990s, leaving a wage gap that cannot be explained by observable gender differences (Blau and Kahn, 2000, 2007; Goldin, 2006). Moreover, due to remaining gender differences in expected household labor (which we discuss in the following subsection), female labor force participation at the intensive margin (hours worked) still trails behind that of men. It is also worth noting that while there is already a "reversed gender gap" in educational level, most notably in collegiate education (Blau and Kahn, 2017), that significantly facilitated the increase of female representation in traditionally male-dominated high-skilled occupations, there is still a considerable gap in occupational distribution, with women remaining overrepresented in fields such as healthcare and education and underrepresented in STEM-related

[2]For example, advances in information technology greatly opened up the possibility of clerical work for women in the early 20$^{\text{th}}$ century (Goldin, 2006).

[3]Blau and Beller (1988) found evidence of a gender convergence of earnings as early as 1971 while Goldin and Polachek (1987) proposes 1980 as the turning point.

occupations (Blau et al., 2013; Hegewisch and Hartmann, 2014).[4]

Similar patterns in gender differences have also been found in other industrialized countries: Olivetti and Petrongolo (2016) found generally upward trends in female labor hours as well as wages relative to men since the 1970s that started to slow down in the 1990s in their sample of high-income countries; and O'Reilly et al. (2015) documented persistence of gender wage gaps in the UK, Europe, and Australia since the 2000s. Therefore, although our analysis is based on US data, the issues explored in our paper could contain implications beyond the US economy.

Previous studies have explored possible contributing factors to the remaining gender gap in wages. While some traditional explanations such as educational attainment (however, studies have found that segregation in terms of college majors remain (England and Li, 2006; Bronson, 2014)) and union participation have little remaining weight in the discussion, other factors such as gender-specific differences in discrimination[5], cognitive skills (performance in math tests in particular[6]) and experience (Blau and Kahn, 2007; Munasinghe et al., 2008) remain as possible explanations. A newer strand of literature investigating the psychological and noncognitive differences between genders have also provided insights into the remaining gap though more work outside the scope of surveys and laboratories might be needed (Blau and Kahn, 2017). Examples include but are not limited to Mueller and Plug (2006), Reuben et al. (2015), and Nyhus and Pons (2012).[7]

2.2 The Relationship between Earnings & Hours - Nonlinear Wage Structures

In our study, we mainly follow the line of work that examines the relationship between occupations, hours, and wages and pay particular attention to how temporal flexibility (or lack thereof) in the labor market interacts with uneven gender roles to create distortions.

Goldin (2014) offers a narrative where wage structures, in particular, the nonlinearity of pay in hours worked, could be the key to concluding the last figurative chapter of the grand gender convergence in wages. Workers in certain high-income occupations are often rewarded for working long, inflexible hours,

[4]While women made significant progress in traditionally male-dominated occupations, no similar influx of men into predominantly female occupations were observed.

[5]Conclusive evidence for the effects or even the existence of discrimination is difficult to obtain by statistical inference. Blau and Kahn (2017) provides an overview of past statistical as well as experimental research within this domain.

[6]Pope and Sydnor (2010) found evidence of a gender gap in the performance of mathematics tests, though they did not examine its relation to gender gaps.

[7]Blau and Kahn (2017) provides a thorough literature survey of different factors related to the remaining gender wage gap.

and suffer lower hourly returns for decreasing their work hours. Common characteristics of these occupations include the necessity of face-to-face interactions or individual-specific tasks. Because of these traits, employees are far from perfect substitutes for each other and thus a slight cutback in labor hours or even a switch to remote work would drastically reduce the firm's productivity. Thus, from a personnel economics perspective, firms derive less marginal utility from workers who work shorter hours and would offer them lower remunerations. Goldin argues that given the persistent differences in housework division, revolutionizing high-income occupations such that they no longer have an incentive to disproportionately compensate for long hours is the key to closing the remaining gender wage gap. Goldin cites pharmacy as an example of a high-skilled industry that succeeded in minimizing the gender wage gap by offering linear compensations to hours worked.[8]

A growing literature has found evidence of nonmonotonic returns to work hours in line with Goldin (2014)'s narrative. Aaronson and French (2004) and Ameriks et al. (2020) found negative effects of part-time work on wages compared to full-time work. Cha and Weeden (2014) looked into the rising prevalence of overwork and estimated that its effects could constitute 10 percent of the remaining gender wage gap. Bick et al. (2022) found penalties in wages for less-than-full-time workers as well as for those who work over 50 hours in a static setting.

However, studies in static settings can only account for within-occupation variations to a limited degree for rewards for long working hours often emerge over the life cycle. For example, an individual that worked extended hours when they were young could have increased opportunities for promotion later on in life, thus achieving higher income levels over the life cycle. Studies on the dynamic effects of hours on wages yielded results that support the hypothesis of an enhanced nonlinearity in the wage structure when we consider long-term labor market outcomes of agents (Imai and Keane, 2004; Michelacci and Pijoan-Mas, 2012). Bertrand et al. (2010)'s study of top-school MBA graduates also found gender differences in career interruptions and hours worked (both of which are associated with motherhood) to be important for the gender wage gap.

Moreover, cross-occupational differences in the degree of nonlinearity are also an important component of our framework that affects occupational choice through gender differences in time allocation. Cortes and Pan (2016) concluded that high returns to long hours coupled with gender differences in the tendency of working long hours significantly contributed to the gender wage gap, especially for highly-educated workers. Adda et al. (2017) and Dustmann and Meghir

[8]Goldin and Katz (2016) investigated the characteristics of the pharmaceutical industry and concluded that improved substitutability of workers due to technological advances as well as a reduced premium to ownership (linked to the rise of large pharmacy chains) contributed to making it a "family-friendly" occupation.

(2005) have also found heterogeneous degrees of lifetime returns across different skill groups of occupations.

Previous studies related to the trends in housework hours have documented that women in general still bear a heavier burden of housework despite a dramatic decline in housework hours compared to the 1960s (Bianchi et al., 2000, 2012; Sayer, 2010). Therefore, as we reasoned in the previous section, women are less likely to pursue careers in nonlinear occupations where high or inflexible work hours are generously remunerated; and those who do pursue these careers often face lower hourly returns than their colleagues due to lower hours worked. When this distortion in occupation choice affects a large portion of the labor force, it can lead to significant aggregate consequences, or misallocation effects, in the economy.

2.3 Talent Misallocation

Talent misallocation caused by gender differences has been found to have important aggregate consequences by previous studies. Hsieh et al. (2019) estimate that the convergence in the occupational distribution across races and genders can account for 15 to 20 percent of the growth in aggregate output per worker in the United States between 1960 and 2008; Lee (2022) estimates that total market and home output would have been 3.5% lower in 2010 if the gender norms related to marriage remained at the level of 1940. Cross-country studies have found that productivity losses due to gender inequality exist across countries as well (Ugarov et al., 2019; Monge-Naranjo et al., 2018).

Erosa et al. (2022) conducted a model-based analysis to quantify the talent misallocation effects of Goldin (2014)'s narrative regarding the role of nonlinear wage structures. They quantify and add to Goldin's narrative by conducting their analysis through the lens of a modified Roy (1951) occupational choice model that includes an intensive margin of labor supply as well as a nonlinearity in earnings (in the sense that the total earnings - hours function is nonlinear/convex until a certain point of hours where it becomes linear).

Our study contributes to existing literature in the following ways: First of all, our model features a nonlinear wage structure that allows us to examine the extent to which interaction between temporal flexibility and uneven gender roles leads to talent misallocation in the economy; While Erosa et al. (2022) also feature nonlinearity in wages in their model, we differentiate our work by including household production decisions in the model, which adds an extra dimension in terms of time allocation; Moreover, our study features a collective model of household in line with the one developed by Chiappori (1992). Erosa et al. (2022) uses a non-unitary model where preferences are equally weighted while our approach allows Pareto weights to vary. Thus, we are able to capture the effect of intra-household allocation of resources in our model.

3 Data & Motivating Facts

This section presents data and facts that are central to our analysis. We mainly base our study on the IPUMS Current Population Survey (IPUMS CPS) files[9] and use the Panel Study of Income Dynamics (PSID) family and individual database[10] to supplement for information concerning housework and within-household correlations.

We observed dispersions in mean annual hours worked and mean (real) hourly wages across occupations that are in line with previous literature (Erosa et al., 2022). We also noted substantial gender gaps in terms of occupational distribution, hours worked, and hourly wages after controlling for occupation that are in line with previous literature (Erosa et al., 2022). Note that the data used in Erosa et al. (2022) was for the period 1986-1995, nearly 25 years prior to ours. The fact that gender gaps are similar in these two periods supports the notion that there is a slowdown in the gender convergence and confirms the existence of a remaining gap. Additionally, we present facts about gender differences in housework hours and highlight the role of gender differences in time allocation.

3.1 Data

The IPUMS CPS dataset contains annual household-level cross-sectional survey data on the US labor force from 1962 onward. For analyses that use this data set in the rest of the paper, we use pooled data from the 2010-2019 period unless otherwise specified. We restrict the sample to individuals aged 22-64 who worked at least one week in the year before the survey and at least one hour per week on average. Since we are mainly concerned about gender differences related to household responsibilities, we restrict our sample to married or cohabiting couples who are in the same household (we do not distinguish between marriage and cohabitation). We then construct our key variables - annual hours worked and real hourly wages from information on weeks worked in the year prior to the survey and usual hours worked per week. We keep only those who do not have farm or business incomes and exclude observations with extreme values (top and bottom 0.2%) in terms of annual hours and real hourly wages. In the following two subsections, we exploit the large quantity of this data set to extract information about occupational distribution, labor hours, and wage rates by occupation and gender.

[9]University of Minnesota (2022): https://doi.org/10.18128/D030.V10.0

[10]University of Michigan, Ann Arbor (2022): https://psidonline.isr.umich.edu/default.aspx

We supplement our analysis with the PSID data set, which is collected through longitudinal household surveys conducted annually from 1968 to 1997 and biannually after 1997. We mainly utilize the dataset to supplement IPUMS CPS to extract information related to housework and within-household correlations. We apply the same restrictions as we did for the main CPS data to extract individual information. For within-household moments, we further restrict the sample to heterosexual couples (married or cohabiting) that have both worked at least 1 hour in the past year.

For the rest of the paper, we conduct analysis using pooled IPUMS-CPS data and take individual lifetime means of the PSID data set for the period between 2010 and 2019 unless otherwise specified. We decided on this period because it reflects recent labor market conditions while containing a large enough sample to allow for analyses by occupation (2010 census basis four-digit occupation codes). The reason we did not select a more recent sample was to avoid disruptions caused by the COVID-19 pandemic both in the labor market as well as in the data collection of the survey in 2020. When we conduct analyses by groups (by occupation and gender or by age and gender depending on the grouping method used in each analysis), we only keep groups with more than 30 observations to ensure the quality of the moments obtained.

3.2 Relationship Between Wages and Hours

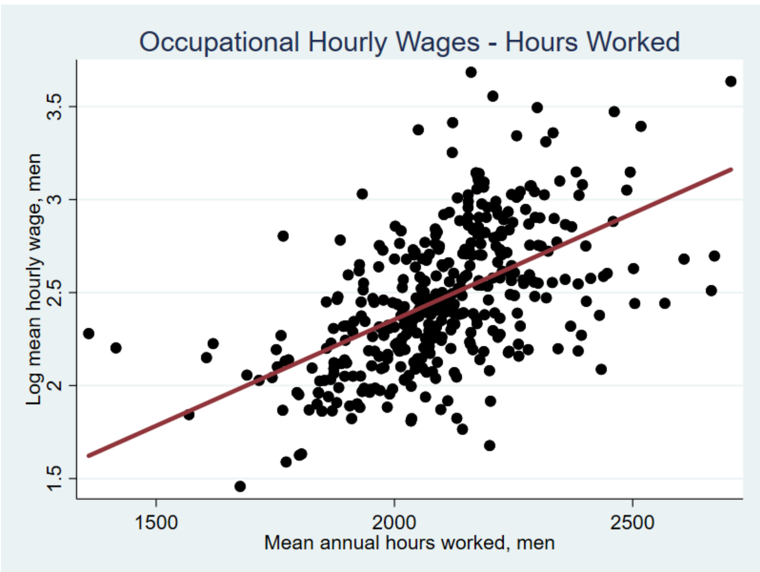

Figure 1: Mean Annual Hours & Mean Hourly Wages, by occupation, 2010-2019

As shown in Figure 1, there is a large variance in mean annual hours worked among occupations even when we restrict the sample to only male workers (thus taking away gender-specific effects). Occupational mean annual hours for men range from less than 1000 hours to more than 2500 hours per year. Moreover, there is a positive correlation between log mean hourly wage and mean annual hours for different occupations, supporting the notion that higher-paying occupations tend to also be ones requiring longer hours of work. Erosa et al. (2022) have shown in their analysis that the distribution of hours worked for men has remained largely unchanged between the 1986-1995 period and 2006-2015.

3.3 Gender Differences in Occupations, Hours, Wages, and Housework

From our data, we observed considerable gender gaps in occupation, hours, wages, and housework participation that are in line with evidence presented in Goldin (2014) and Erosa et al. (2022).

Figure 2 shows the cumulative distributions of men and women across occupations, sorted by occupational mean annual hours of men. As shown in the graph, men are more concentrated than women in occupations with higher (male) mean annual hours. While 26.6% of men work in occupations with mean male annual hours greater than 2250, only 17.7% of women work in these occupations. Differences at the lower tail of the distribution can also be observed from the data. 5.8% of women work in occupations with mean male annual hours lower than 1800 while less than 2 percent of men do.[11]

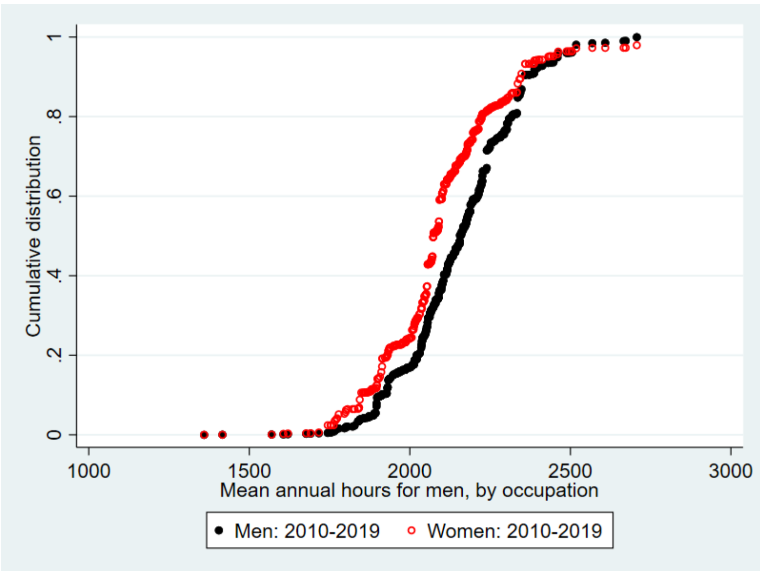

Figure 2: Cumulative Distribution Across Occupations, Men v.s. Women, 2010-2019

Figure 3 shows the relative mean annual hours of women plotted against men. The black line plots men's mean annual hours worked by occupation (inversely sorted by mean annual hours) and each red dot is the corresponding mean annual hours worked for women in that occupation. While occupations where mean annual hours for men are high also tend to be those where mean annual hours

[11]Similar patterns were found in Erosa et al. (2022).

for women are high, the graph paints a clear picture of how, conditional on occupation, women work significantly lower hours on average than men.

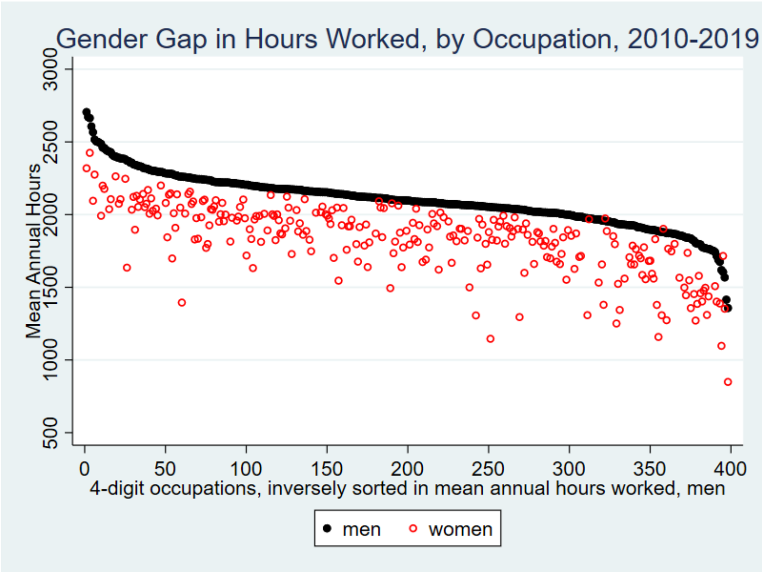

Figure 3: Gender Gap in Mean Annual Hours, by occupation, 2010-2019

Similarly, Figures 4 and 5 plot log mean (real) hourly wages of women against men by occupation for the periods 2010-2019 and 1990-1999 respectively. Again, we observed a clear gender gap in hourly wages by occupation for 2010-2019. It is also evident from comparing the two graphs that while the gender difference in wages after accounting for occupation has decreased since the 1990s, the gap is far from gone.

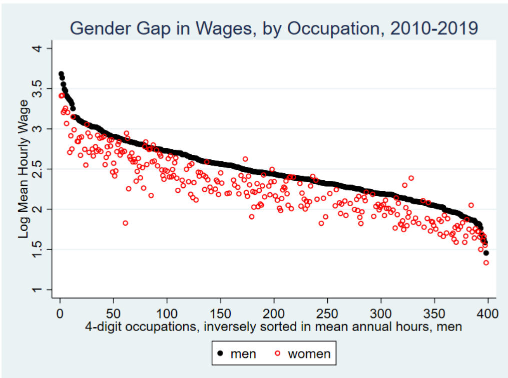

Figure 4: Gender Gap in Log Mean Hourly Wages by Occupation, 2010-2019

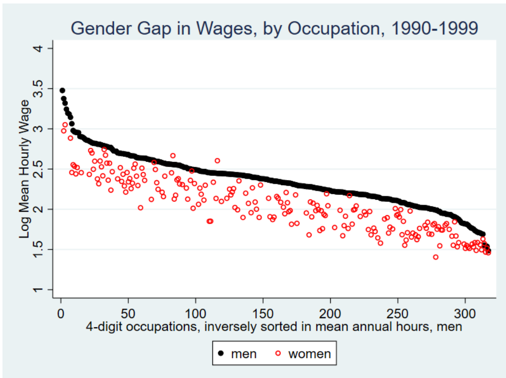

Figure 5: Gender Gap in Log Mean Hourly Wages by Occupation, 1990-1999

In terms of housework hours, we observe a clear gender difference at the aggregate across all ages.[12] This is in line with our expectations that there exists a clear gender difference in housework hours worked even in modern society.

[12]Due to the limited sample size of the PSID compared to the IPUMS CPS files, analyses by occupation are not feasible since each occupation would have too few observations.

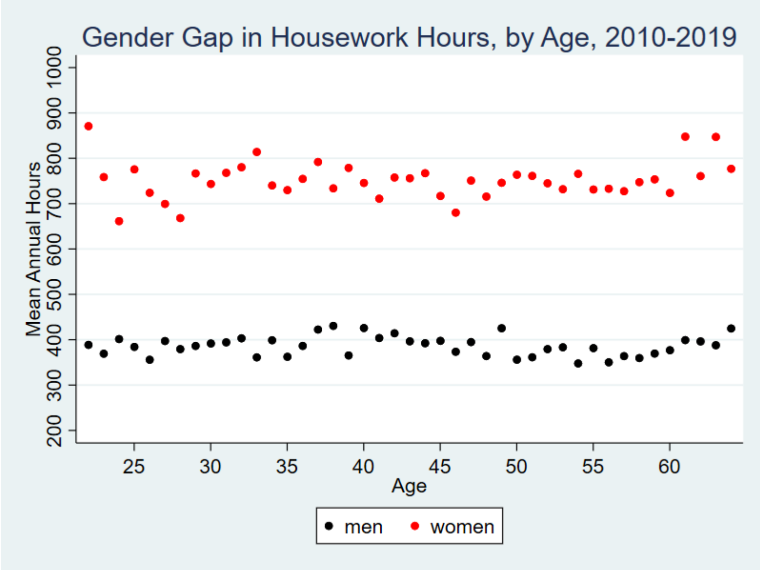

Figure 6: Gender Gap in Annual Housework Hours, 2010-2019

3.4 Nonlinear v.s. Linear Occupations

We aggregate our sample from IPUMS CPS data into two groups following Erosa et al. (2022)'s method: We first rank all occupations in our sample according to mean male annual hours worked; we then split the sample into two groups that are (approximately) equal in size (men plus women) according to occupational mean annual hours worked of men. Matching terminology used by Goldin (2014) and Erosa et al. (2022), we refer to occupations belonging to the group with higher mean annual hours of men as nonlinear occupations (later linked to occupation 1 in our model section), and those in the other group as linear occupations (linked to occupation 2).

Key moments derived from aggregating the economy into two occupation groups are presented in Table 1. Since CPS data is cross-sectional, we adjust for lifetime corrections of moments for the standard deviations of hours and wages. We do so using findings from Erosa et al. (2022) and Erosa et al. (2016), and adjust the cross-sectional variation of hours by a factor of two-thirds and wages by 0.9 to obtain lifetime moments. This preliminary analysis supports our notion that men are more densely distributed in nonlinear occupations while women tend to be in linear occupations. Moreover, in support of our expectation that high-return occupations also tend to be those that require longer hours, mean wages in nonlinear occupations are higher than in linear occupations for both men and women.

While nonlinearities of pay within occupations are central to our study, it is difficult to demonstrate with our main sources of data.[13] As discussed in the

[13]Studies have found nonlinearity of earnings in hours to be more prominent over the life cycle (Imai and Keane, 2004; Michelacci and Pijoan-Mas, 2012). However, our main data source, the IPUMS CPS files, is cross-sectional and thus does not allow for lifetime inference.

Table 1: Data Moments (2010-2019)

	Employment share	Log mean hours	Log mean wages	Sd. of log hours	Sd. of log wages
Male					
Nonlinear	0.62	7.73	2.79	0.23	0.60
Linear	0.38	7.59	2.28	0.32	0.55
Aggregate	1.00	7.68	2.63	0.27	0.62
Female					
Nonlinear	0.38	7.60	2.57	0.34	0.61
Linear	0.62	7.45	2.15	0.44	0.55
Aggregate	1.00	7.51	2.33	0.41	0.60

Notes: the standard deviations of log hours and log wages are lifetime-adjusted.

previous section, past literature has provided evidence of nonmonotonic returns to hours within occupations as well as differential degrees of nonlinearity across occupations. Empirical results from past studies we utilize as a basis for our quantitative analysis include the following: In line with Erosa et al. (2022)'s method of modeling nonlinearity, we follow Bick et al. (2022)'s findings, which suggests a convexity in earnings to hours worked until around 50 hours per week. In terms of occupational differences in nonlinearity, we mostly follow Erosa et al. (2022)'s rationale, which in turn derives from earlier works such as Aaronson and French (2004), Cortes and Pan (2016), Gicheva (2013), Bertrand et al. (2010), Sullivan (2010), Stinebrickner et al. (2018), and Stinebrickner et al. (2019).

4 Model

In this section, we develop a static model that features a nonlinear payment structure and labor supply choice. We start by considering a model of single-member households. We modify the standard Roy (1951) model to incorporate home production, heterogeneous preferences of leisure, and nonlinearity of efficiency units of labor. In this model, individuals allocate time between market work, home production, and leisure, and choose between two occupations to maximize utility. We assume the supply of efficiency units of labor as the one adopted by Erosa et al. (2022), where working hours have an occupation-specific positive effect on wages. We then extend this model to multi-member households. We model the household in a nonunitary setting, and introduce a social norms term

While the supplementary database, PSID, is longitudinal, the sample size becomes insufficient for analyses by occupation after sample selection.

to study the interaction effect of the nonlinear payment structure and uneven divisions of household labor. Gender differences in our model are captured by both occupation-specific mean differences in ability that could feature barriers in accumulating human capital and gender discrimination in wages, and norms against female labor force participation.

4.1 Time Allocation and Occupational Choice

Single Individuals

We assume a continuum of single individuals indexed by j. Individuals have time endowment T and decide how to allocate time between market work, housework, and leisure, and which occupation to be employed in given their abilities and preferences. Total time is allocated between leisure l_j, market working time h_j, and home production time t_j. The utility function is given by:

$$u_j(q_j, l_j, Q) = \ln q_j + \beta_j \ln Q + \phi_j \frac{(l_j)^{1-\gamma}}{1-\gamma} \tag{1}$$

where q_j is the consumption of the private good produced with market hours, Q denotes the consumption of the public good[14] produced with home hours, l_j is the leisure time, and γ determines the curvature in utility gained from leisure. We assume the preference for leisure ϕ_j and the preference for the public good (home production) β_j vary across individuals, thus heterogeneous preferences are included as a potential source of differences in time allocation. Moreover, individuals have heterogeneous abilities in occupation 1, occupation 2, and home production, denoted by $b_{j,1}$, $b_{j,2}$, and a_j respectively. And we assume that heterogeneity across individuals is described by $(b_{j,1}, b_{j,2}, a_j, \beta_j, \phi_j)$ and is drawn from a multivariate log-normal distribution.

For an individual with productivity parameter b_k in occupation k that works h hours in occupation k, her efficiency units of labor in occupation k is given by:

$$w_k(h) = b_k g_k(h) \tag{2}$$

We assume $g_k(h)$ is given by the following step-functions proposed by Erosa et al. (2022):

$$g_k(h) = \begin{cases} h^{1+\theta_k}\ , \ h \leq \bar{h} \\ B_k h\ ,\ h \geq \bar{h} \end{cases} \tag{3}$$

where we choose $B_k = \bar{h}^{\theta_k}$ to make $g_k(h)$ continuous. This function implies

[14] The terminology public good here refers to goods that can be nonrival in multi-member households.

that the mapping from individual hours worked to the supply of efficiency units of labor is nonlinear (convex) if hours worked are below $\bar{h}$ and constant in the region $h > \bar{h}$. The nonlinearity is characterized by the parameter θ_k. We assume $\theta_1 > \theta_2$ to reflect that earnings in occupation 1 display a greater nonlinearity. In terms of home production, we assume a linear technology[15] for single individual households. The total production/consumption of the home good is equal to the efficiency units of home time.

In what follows we normalize the price of the private good and the technology parameter in both occupations to unity[16], thus the individual's decision can formally be described by the following utility maximization problem:

$$\max_{h_j, t_j, l_j, I_j^k} u_j(q_j, l_j, Q)$$

subject to

$$q_j = \sum_{k=1}^{2} I_j^k w_k(h_j)$$

$$Q = a_j t_j$$

$$T = h_j + t_j + l_j$$

$$\sum_{k=1}^{2} I_j^k = 1, I_j^k = 0 \text{ or } 1$$

The optimal labor supply problem can be solved in two steps. Individuals first allocate time conditional on occupational choice, and then choose between two occupations to maximize utility. To grasp the properties of the model, we consider the case where $\bar{h}$ is sufficiently large such that $h < \bar{h}$ always holds. In this case, the first-order conditions for the time allocation problem conditional on occupational choice are given by:

$$\frac{1+\theta_k}{\phi_j} = h_{j,k}(l_{j,k})^{-\gamma} \tag{4}$$

$$\frac{\beta_j}{\phi_j} = t_{j,k}(l_{j,k})^{-\gamma} \tag{5}$$

for $k = 1, 2$. Combining these two conditions yields

$$\frac{h_{j,k}}{t_{j,k}} = \frac{1+\theta_k}{\beta_j} \tag{6}$$

Several properties are as follows: First, $h_{j,k}$ and $t_{j,k}$ are independent of oc-

[15] We assume that households only need to use time as input for home production. Thus the public good here we refer to is more about home activities like cleaning, child care and so on.

[16] Thus in a competitive equilibrium price of an efficiency unit of labor will be equal to unity. See details in the firm section

cupational productivity $b_{j,k}$ and home productivity a_j. Time allocation between the three activities is determined by the nonlinearity parameter θ_k, leisure preferences ϕ_j, and public good preferences β_j. Second, market hours and home hours both decrease as ϕ_j increases. A higher value of ϕ_j implies a higher utility of leisure, thus time spent on production is decreasing in ϕ_j. Third, an increase in θ_k leads to an increase in the ratio of market hours over home hours. The magnitude of θ_k shows the extent to which an increase in working hours could increase hourly earnings from occupation k. It can be shown that $h_{j,k}$ would increase as θ_k increases. Fourth, an increase in β_j would decrease the ratio of market hours over home hours. Individuals who prefer home production more would spend relatively more time on it. To summarize, the cross-sectional variation in working hours within an occupation is driven by heterogeneity in preferences.

An individual would choose to work in occupation 1 if the following inequality holds:

$$\ln(b_{j,1}h_{j,1}^{1+\theta_1}) + \beta_j \ln(a_j t_{j,1}) + \phi_j \frac{(l_{j,1})^{1-\gamma}}{1-\gamma} > \ln(b_{j,2}h_{j,2}^{1+\theta_2}) + \beta_j \ln(a_j t_{j,2}) + \phi_j \frac{(l_{j,2})^{1-\gamma}}{1-\gamma}$$

where $h_{j,1}, h_{j,2}, t_{j,1}, t_{j,2}$ are the solutions to equation (6). Using (4), (5), and (6), this expression can be simplified to

$$\begin{aligned} \ln(\frac{b_{j,1}}{b_{j,2}}) > \quad & z(\phi_j, \beta_j) \\ \equiv \quad & -(1+\beta_j+\theta_1)\ln(h_{j,1}) + (1+\beta_j+\theta_2)\ln(h_{j,2}) \\ & + \beta_j(\ln(1+\theta_1) - \ln(1+\theta_2)) \\ & + \phi_j \left[\frac{\left(T - \frac{1+\beta_j+\theta_1}{1+\theta_1} h_{j,1}\right)^{1-\gamma}}{1-\gamma} - \frac{\left(T - \frac{1+\beta_j+\theta_2}{1+\theta_2} h_{j,2}\right)^{1-\gamma}}{1-\gamma} \right] \end{aligned} \tag{7}$$

Equation (7) shows that occupational choice is jointly determined by comparative advantage (log ratio of skills in the two occupations), preferences for leisure, and preferences for home production. Given that $\theta_1 > \theta_2$, the optimal market hours would be longer in occupation 1 than in occupation 2. Hence, holding all else constant, an increase in the taste for leisure would make an individual less likely to choose occupation 1. The effect of a change in β_j, however, is ambiguous and cannot be obtained directly.

If $\bar{h}$ is not sufficiently large, the optimal market hours suggested by the above FOCs might fall in the region where $h > \bar{h}$. And $h_1 > \bar{h}$ is more likely to happen since $\theta_1 > \theta_2$ results in $h_1 > h_2$. In this case, the optimal hours of working may be $h = \bar{h}$ or $h > \bar{h}$. Given a constant hourly wage when $h \geq \bar{h}$, the optimal hours would be lower than what the above FOC suggests. Thus for a given distribution of preferences, $\bar{h}$ would compress the working hours toward $\bar{h}$, especially for occupation 1. Moreover, equation (6) implies that the time spent on home production would also be affected by $\bar{h}$. In the region where $h_k > \bar{h}$, θ_k would be zero. Thus the ratio of market hours over home hours would be directly affected. Home hours become relatively preferred than the case where $\bar{h}$ does not play a role.

To summarize, heterogeneity in preferences for leisure and home production drive heterogeneity in time allocation. And occupation-specific nonlinearities create heterogeneity in the desired level of market work hours across occupations as well as lead to different trade-offs between market work and home production. For given values of θ_k, the occupational choice is jointly determined by the comparative advantage, optimal hours in two occupations, preferences for leisure, and preferences for home production. Thus, social norms against female labor supply may distort time allocation which in turn affects occupational sorting. We next extend this model to married individuals and discuss how social norms might affect households' decisions.

Married Individuals

For married individuals, we consider a collective household model (Chiappori, 1992) that assumes an efficient allocation of intra-household resources.[17] Each household is composed of a male i and a female j, and the Pareto weight on female utility is denoted by λ_{ij}. λ_{ij} captures the female member's bargaining power in intra-household resource allocation, and varies with the characteristics of households. The household as a union makes occupational choices, allocates time between the labor market, home production, and leisure, and determines how total private consumption is divided. A household's utility is given by:

$$U(q_i, q_j, l_i, l_j, Q, h_j) = (1 - \lambda_{ij})[u_i(q_i, l_i, Q)] + \lambda_{ij}[u_j(q_j, l_j, Q)] - \zeta h_j \tag{8}$$

where

$$u_g(q_g, l_g, Q) = \ln q_g + \beta_g \ln Q + \phi_g \frac{(l_g)^{1-\gamma}}{1-\gamma}, \;\; g = i, j$$

q_g $(g = i, j)$ denotes the consumption of the private good, Q denotes the shared public good, l_g denotes leisure time, β_g denotes idiosyncratic preferences for public good, and ϕ_g represents idiosyncratic preferences for leisure. The last term in the utility function represents the disutilities of married women participating in market work, where ζ measures the degree of social norms that discourages female labor supply. Heterogeneity across households is described by

[17] Previous literature has studied labor supply in non-unitary household models (See summary in Donni and Chiappori (2011)). We use a cooperative model based on the hypothesis that the decision process within the household leads to Pareto-efficient outcomes. Our model is able to reflect the relationship between intra-household resource allocation and labor supply. Moreover, this collective model can be extended further to incorporate a marriage market where a set of Pareto weights across households clears the marriage market. We would like to explore this possibility in future works.

$(b_{i,1}, b_{i,2}, a_i, \beta_i, \phi_i, b_{j,1}, b_{j,2}, a_j, \beta_j, \phi_j)$ and is drawn from a multivariate log-normal distribution. We allow the mean value of market productivity to differ for men and women, reflecting differences in human capital or wage gap caused by discrimination.

We normalize the price of the private good to unity without loss of generality. It follows that the hourly pay of one unit of efficiency labor would be equal to the technology parameter. Setting the technology parameter to unity, the household's maximization problem becomes:

$$\max U(q_i, q_j, l_i, l_j, Q, h_j)$$

subject to

$$q = q_i + q_j = \sum_{m=1}^{2} I_i^m w_m(h_{i,m}) + \sum_{k=1}^{2} I_j^k w_k(h_{j,k})$$

$$q_j = sq$$

$$Q = [\alpha(a_i t_{i,m})^\sigma + (1-\alpha)(a_j t_{j,k})^\sigma]^{\frac{1}{\sigma}}$$

$$T = h_{i,m} + t_{i,m} + l_{i,m} = h_{j,k} + t_{j,k} + l_{j,k}$$

$$\sum_{m=1}^{2} I_i^m = \sum_{k=1}^{2} I_j^k = 1$$

where $I_i^m = 1 (m = 1, 2)$ if male i works in occupation m and $I_i^m = 0$ if not; $I_j^k = 1 (k = 1, 2)$ if female j works in occupation k and $I_j^k = 0$ if not. The efficiency units of labor $w(h)$ is given by equations (2) and (3), and again $\theta_1 > \theta_2$ is set so that occupation 1 features greater nonlinearity. Note that we assume a CES home production function that features a constant elasticity of substitution between male efficiency units of home time and female efficiency units of home time.

In our preference specification, the first-order conditions yield that the private good consumption share s is independent of the total household private good consumption and is equal to the Pareto weight λ_{ij}. Thus the optimal allocation of consumption suggests $(1-\lambda_{ij})q_j = \lambda_{ij} q_i$. We can then derive the optimal choice of labor hours conditional on occupational choices. Again, here we consider the case where $\bar{h}$ is sufficiently high so that market hours $h_{j,k}$ and $h_{i,k}$ are both positive and less than $\bar{h}$. Conditional on occupational choices, the first-order conditions are as follows:

$$\begin{aligned}
\frac{b_{i,m}(1+\theta_m)h_{i,m}^{\theta_m}}{b_{i,m}h_{i,m}^{1+\theta_m}+b_{j,k}h_{j,k}^{1+\theta_k}} &= (1-\lambda_{ij})\phi_i(T-t_{i,m}-h_{i,m})^{-\gamma} \\
\frac{b_{j,k}(1+\theta_k)h_{j,k}^{\theta_k}}{b_{i,m}h_{i,m}^{1+\theta_m}+b_{j,k}h_{j,k}^{1+\theta_k}}-\zeta &= \lambda_{ij}\phi_j(T-t_{j,k}-h_{j,k})^{-\gamma} \\
\frac{((1-\lambda_{ij})\beta_i+\lambda_{ij}\beta_j)\,\alpha\sigma a_i^{\sigma}t_{i,m}^{\sigma-1}}{\alpha(a_i t_{i,m})^{\sigma}+(1-\alpha)(a_j t_{j,k})^{\sigma}} &= (1-\lambda_{ij})\phi_i(T-t_{i,m}-h_{i,m})^{-\gamma} \\
\frac{((1-\lambda_{ij})\beta_i+\lambda_{ij}\beta_j)\,(1-\alpha)\sigma a_j^{\sigma}t_{j,k}^{\sigma-1}}{\alpha(a_i t_{i,m})^{\sigma}+(1-\alpha)(a_j t_{j,k})^{\sigma}} &= \lambda_{ij}\phi_j(T-t_{j,k}-h_{j,k})^{-\gamma}
\end{aligned} \tag{9}$$

The first-order conditions imply that the male member of the household chooses market hours and home hours to equalize a) his marginal utility of leisure multiplied by his Pareto weight, b) his marginal increase in earnings multiplied by the marginal utility of household private consumption, and c) the marginal increase in home production multiplied by the marginal utility of household public consumption. The female member equates a) her marginal utility of leisure multiplied by her Pareto weight, b) her marginal increase in earnings multiplied by the marginal utility of household private consumption, minus the marginal disutility of market hours due to social norms, and c) the marginal increase in home production multiplied by the marginal utility of household public consumption.

Several properties of the model are as follows. First, the trade-off between market work and home production is associated with preferences for public good β, but is unrelated to preferences for leisure ϕ. However, ϕ determines the allocation between leisure and production activities directly. Holding the other member's choices fixed, time spent on both production and home production is (almost always) decreasing in the value of ϕ. Second, choosing the occupation with higher θ implies higher working hours. Since higher female working hours would impose higher levels of disutility for households, females are relatively more constrained from working in occupation 1. The uneven division of social responsibilities impedes women from working longer hours, and this effect is larger in occupations that have less temporal flexibility. Third, there are cross-effects within couples on both labor supply and home production. An increase in the earnings of one spouse would decrease the marginal utility of income earned by another member. As a result, the other household member would reduce time spent on market work and would be less likely to choose occupation 1. Further, an increase in the home hours of one spouse would similarly decrease the home hours of another spouse. One important thing to note is the close connection between home hours and market hours in our model: Changes in one spouse's time allocation will lead to a composite effect on the other's time allocation, depending on their relative abilities and preferences.

The model implies that the existence of social norms may distort labor supply, time allocation, and occupational choice. And the nonlinearity of the wage structure amplifies these distortions. In a world with constant wages, when women are more heavily burdened with nonmarket responsibilities caused by social norms, they are discouraged from participating in market work compared to men with the same productivity. As a result, there would be a portion of women with high abilities in the labor market who stay at home while some men with lower market abilities than those women work long hours, resulting in a talent misallocation. The nonlinearity of pay would exacerbate the effect of talent misallocation caused by gender inequality compared to constant hourly pay. Since women are more constrained to workplace flexibility, they cannot commit enough market time to work in occupations with high nonlinearity. Thus, some women with high potential productivity in the nonlinear occupation enter into the linear occupation, resulting in further talent misallocation across occupations.

4.2 Firms

In terms of production, we assume a single final good is produced with two different technologies (representing two different occupations) and each technology is linear in efficiency units of labor.

$$Y_k = A_k E_k$$

where Y_k is the total output from occupation k, and E_k is the aggregate input of efficiency units of labor to occupation k. We normalize the technology parameter A_k to unity in all occupations, thus the price of one efficiency unit of labor would be equal to unity. The total output produced in the market is the aggregate of efficiency units of labor:

$$Y_{market} = Y_1 + Y_2 = E_1 + E_2 \tag{10}$$

The total efficiency units of labor in two occupations are given by:

$$\begin{aligned} E_1 &= \int_{i, I_i^1 = 1} b_{i,1} g_1(h_{i,1}) + \int_{j, I_j^1 = 1} b_{j,1} g_1(h_{j,1}) \\ E_2 &= \int_{i, I_i^2 = 1} b_{i,2} g_2(h_{i,2}) + \int_{j, I_j^2 = 1} b_{j,2} g_1(h_{j,2}) \end{aligned} \tag{11}$$

4.3 Equilibrium

An equilibrium in this economy consists of public good consumption Q, private good consumption q, leisure l, home hours t, market hours h_1 and h_2, occupational choice I^k, total efficiency units of labor E_1 and E_2, market wage, market output Y_{market}, total home production Y_{home}, and aggregate output Y, such that

1) After the exogenous determination of preferences and abilities and given wages in each occupation, each household makes time allocation choices and chooses public good consumption Q and private good consumption q to maximize the household's utility.

2) A representative firm hires labor E_1 and E_2 in two occupations, and pays wages equal to effective units of labor.

3) Market output Y_{market} is equal to the sum of efficiency units of labor in the market, and total home production Y_{home} is equal to total efficiency units of home time.

4) The aggregate output of the economy is given by the sum of market output and home production.

5 Calibration and Model Fit

We present our baseline calibration in this section. For the baseline calibration, we divide all parameters that need to be assigned into two sets. Parameters in the first set are chosen exogenously while the other set of parameters is pinned down by solving the model and matching simulated moments to moments from the data.

5.1 Parameter Assumptions

We start by assigning some parameters exogenously. Consistent with our data section, we report all labor supply measures in terms of annual hours. The total time endowment is set to $T = 5460$, implying that 105 hours[18] of discretionary time are available per week. In our baseline calibration, three key parameters reflecting temporal inflexibility/nonlinear wage structure proposed in our model are set as: $\theta_1 = 0.6$, $\theta_2 = 0.2$, and $\bar{h} = 2600$. Our model specification implies that, for each occupation, when the annual hours worked is larger than 2600, the hourly wage stays constant.[19] The value of θ reflects nonlinearity in the wage structure. Due to a lack of existing estimates,[20] we set θ to different values in

[18]This suggests that we assume that nine hours a day are allocated to sleep and refreshing.

[19]Bick et al. (2022) show that hourly wages decrease after 50 hours in the cross-section. On the other hand, Gicheva (2013) finds a dynamic positive effect for weekly hours above 50. The constant hourly wage above the threshold in our setting should be interpreted as a combination of cross-sectional and life-cycle effects.

[20]Erosa et al. (2022) provides some reasoning for the choice of θ.

our sensitivity analysis. We set $\gamma = 4$ such that the intertemporal elasticity of labor along the intensive margin is fixed at a value of $1/4$.

For the remaining parameters, we infer them from matching data moments to empirical moments. We adopt the following assumptions when doing the calibration. First, without loss of generality, the mean value of log male ability in occupation 1 (μ_{b_1}) is normalized to be zero. Also, the mean value of log home production ability (μ_a) production is set to be zero.[21] Second, we assume that preferences (for both leisure and the public good) are uncorrelated with market and home productivity.[22] And preferences for leisure and preferences for the public good are uncorrelated. Third, we assume that an individual's market abilities are uncorrelated with their home productivity. Fourth, the correlation of abilities within spouses is the same in occupations 1 and 2. Fifth, home productivity draws are independent.

To infer Pareto weights for each household, we first calibrate the model with fixed Pareto weights and obtain an "average" Pareto weight.[23] We further allow Pareto weights to vary with households' relative abilities.[24] Intuitively the bargaining power in a household should be related to relative wages within couples. In our model, individuals' wages are determined by their ability, hours of working, and occupation. And the market hours gap between women and men would be directly correlated to social norms in the model. Based on these considerations, we assume λ_{ij} as a reshaped average value of relative abilities:

$$\lambda_{ij} = \frac{1}{2}\left(\frac{b_{j,1}}{b_{j,1}+b_{i,1}} + \frac{b_{j,2}}{b_{j,2}+b_{i,2}}\right)\left(1 - \frac{\zeta}{m_\lambda}\right) \tag{12}$$

where $m_\lambda > \zeta$ is a reshaping parameter to capture the effect of social norms.

The remaining parameters that need to be estimated include: mean value of log male ability in occupation 2 (μ_{b_2}); differences between mean values of log female and male abilities in occupation 1 and 2 ($\Delta\mu_{b_1}$ and $\Delta\mu_{b_2}$); mean value of log preferences for leisure (μ_ϕ); mean value of log preferences for public good (μ_β); variance of log ability in occupations 1 and 2 ($\sigma^2_{b_1}$ and $\sigma^2_{b_2}$); variance of log preferences for leisure (σ^2_ϕ); variance of log preferences for public good (σ^2_β); variance of log home productivity (σ^2_a); correlation of abilities in occupation 1 and 2 (ρ_{b_1,b_2}); correlation between preferences for leisure within couples (ρ_{ϕ_i,ϕ_j}); corre-

[21] In fact, we cannot identify the absolute value of home production, only the variance of home productivity matters for simulated moments.

[22] Assuming additional distribution parameters is possible, but only has limited effects on our results. It would be more clear for us to identify with relatively fewer free parameters. And our current specification is able to match the most important part of data features.

[23] See Appendix B.

[24] Though preferences might also affect households' decision-making process, the simplest intuitive way to vary Pareto weight is using abilities. Also, the calibration results suggest a strong correlation of preferences within couples, thus the influence of preferences won't be decisive.

lation between preferences for public good of within couples (ρ_{β_i,β_j}); correlation of abilities within couples ($\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$); reshaping parameter regarding Pareto weight (m_λ); social norms parameter (ζ); share parameter in CES home production function(α); and substitution parameter in CES function (σ). In total there remain 18 parameters to determine. The equilibrium outcome is jointly determined by all parameters, and we calibrate these parameters by matching moments that link closely with labor supply patterns, time allocation, and gender differences.

5.2 Targeted Moments

Our targeted moments include:

- The share of male/female employment in occupation 1 (S^1_m, S^1_f)
- log mean hours of market work by men and women ($\ln h_m, \ln h_f$)
- log mean hours of housework by men and women ($\ln t_m, \ln t_f$)
- The standard deviation of log male hourly wages by occupations ($\mathrm{sd}(\ln w_{m,1})$, $\mathrm{sd}(\ln w_{m,2})$)
- The standard deviation of log market hours of by men and women ($\mathrm{sd}(\ln h_m)$, $\mathrm{sd}(\ln h_f)$)
- The standard deviation of log home hours by men and women ($\mathrm{sd}(\ln t_m)$, $\mathrm{sd}(\ln t_f)$)
- The mean difference in male/female log hourly wages between occupation 1 and 2 ($\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}, \ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$)
- The correlation of log leisure/home hours within households (corr_{l_m,l_f}, corr_{t_m,t_f})
- The correlation of log hourly wages within households (corr_{w_m,w_f})
- The mean difference in gender log wages ($\ln \bar{w}_m - \ln \bar{w}_f$)

Although there is no one-to-one relationship between parameters and moments, each parameter is closely connected to several sensitivity moments. We list parameters and the corresponding sensitivity moments in Table 2. We discuss the connection between parameters and targeted moments below:

Abilities. Parameters related to abilities mainly decide the comparative advantage and absolute advantage, thus affecting occupational choices and optimal hours. The log mean value of ability in occupation 2 μ_{b_2} is closely connected to the share of employment in occupation 1. Since we normalize the log mean value of ability in occupation 1 to be zero, μ_{b_2} would determine average relative earnings, thus the share of employment in each occupation. The gender differences in abilities ($\Delta\mu_{b_1}$, $\Delta\mu_{b_2}$) are closely connected to the share of female employment in occupation 1, market hours, gender wage gap, and female wage gap across occupations. The relative magnitude of $\Delta\mu_{b_1}$ and $\Delta\mu_{b_2}$ determines comparative advantage, and the absolute magnitude of $\Delta\mu$ direct affects the gender wage gap. The variance of market ability ($\sigma^2_{b_1}, \sigma^2_{b_1}$) is closely connected to the standard deviation of log wages in the data. The variance of home ability is closely connected to the standard deviation of home hours. The standard Roy model suggests that the correlation of abilities (ρ_{b_1,b_2}) will affect the selection of individuals into occupations by overall ability and therefore affect the mean wage gap across occupations. Moreover, ρ_{b_1,b_2} will also affect the correlation of leisure, home hours, and wages within couples by influencing occupational choice and intra-household time allocation. The correlation of abilities within couples ($\rho_{b_{i,1},bj,1} = \rho_{b_{i,2},bj,2}$) will be linked to occupation choices and time allocation, thus will affect the correlation of hours and wages.

Preferences. Preference parameters mainly determine how households allocate time between market work, home production, and leisure. Preferences for leisure are closely connected to market hours and home hours since μ_ϕ directly affects the trade-off between production activities and leisure. The preference for public good μ_β is closely connected to time spent on home production. The variance of preferences (σ^2_ϕ, σ^2_β) directly affects the standard deviation of corresponding hours. The correlation of preferences (ρ_{ϕ_i,ϕ_j}, ρ_{β_i,β_j}) is closely connected to the correlation of hours.

Substitutability, Pareto Weights and Norms. Remaining parameters are important in shaping structural gender asymmetries in the model. Social norms (ζ) against female labor supply are directly connected to women's working hours. The reshaping parameter m_λ affects the bargaining power in a family together with ζ and thus is closely connected to time allocation in a family. The last two parameters are the parameter (α) and substitution parameter (σ) in the CES home production function. σ captures the share of labor input in home production, and α captures the extent to which home labor inputs can be substituted between spouses. Thus α and σ are both closely connected to moments related to home hours.

5.3 Calibration Results

We calibrate our model by minimizing the sum of the square of differences between the above-listed moments in the model and in the data. Details are shown in Appendix A and B. Table 3 presents the calibrated parameters and the targeted moments in the data and in the model.

Table 2: Parameters and Relevant Moments

Parameters	Sensitivity Moments
μ_{b_2}	S^1_m, S^1_f
$\Delta\mu_{b_1}$	$S^1_f, \ln h_m, \ln h_f, \ln \bar{w}_m - \ln \bar{w}_f, \ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$
$\Delta\mu_{b_2}$	$S^1_f, \ln h_m, \ln h_f, \ln \bar{w}_m - \ln \bar{w}_f, \ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$
μ_ϕ	$\ln h_m, \ln h_f, \ln t_m, \ln t_f$
μ_β	$\ln t_m, \ln t_f$
$\sigma^2_{b_1}$	$\mathrm{sd}(\ln w_{m,1})$
$\sigma^2_{b_2}$	$\mathrm{sd}(\ln w_{m,2}$
σ^2_ϕ	$\mathrm{sd}(\ln h_m), \mathrm{sd}(\ln h_f)$
σ^2_β	$\mathrm{sd}(\ln t_m), \mathrm{sd}(\ln t_f)$
σ^2_a	$\mathrm{sd}(\ln t_m), \mathrm{sd}(\ln t_f)$
ρ_{b_1,b_2}	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}, \ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}, \mathrm{corr}_{l_m,l_f}, \mathrm{corr}_{t_m,t_f},$ corr_{w_m,w_f}
ρ_{ϕ_i,ϕ_j}	$\mathrm{corr}_{l_m,l_f}, \mathrm{corr}_{t_m,t_f}$
ρ_{β_i,β_j}	corr_{t_m,t_f}
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	$\mathrm{corr}_{l_m,l_f}, \mathrm{corr}_{t_m,t_f}, \mathrm{corr}_{w_m,w_f}$
m_λ	$\ln h_m, \ln h_f, \ln t_m, \ln t_f$
ζ	$S^1_f, \ln h_f, \ln t_f$
α	$\ln t_m, \ln t_f, \mathrm{sd}(\ln t_m), \mathrm{sd}(\ln t_f)$
σ	$\ln t_m, \ln t_f, \mathrm{sd}(\ln t_m), \mathrm{sd}(\ln t_f)$

Overall, our model can fit the targeted moments fairly well. The model is able to closely match the share of male employment in occupation 1 (0.62) by adjusting the mean value of log male ability in occupation 2. Since occupation 1 features greater nonlinearity and potentially higher earnings than occupation 2 for long working hours, it requires μ_{b_2} to take a larger magnitude (2.796) to guarantee occupation 2 is not strictly dominated.[25] The share of female employment in occupation 1 in the model (0.40) is close to the data (0.38). The gender gap in the share of employment in nonlinear occupation mainly comes from social norms ($\zeta = 6.301 \times 10^{-5}$) and different gender skill gaps across two occupations ($\Delta\mu_{b_1} = 0.301, \Delta\mu_{b_2} = 0.014$). This suggests two potential sources of talent misallocation in our model: norms against female working extended hours and skill differences caused by human capital barriers (especially on-the-job training) and wage discrimination.

The log mean hours of market work by men and women in the baseline cali-

[25] The ability is combined with the nonlinear structure to get efficiency units of labor, thus should not be interpreted as individuals in occupation 2 have higher productivity.

Table 3: Calibration of Baseline Economy

Parameter	Value	Target Moments	Data	Model
μ_{b_2}	2.796	S_m^1	0.62	0.62
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.40
$\Delta\mu_{b_2}$	0.014	$\ln h_m$	7.68	7.69
μ_ϕ	24.301	$\ln h_f$	7.51	7.49
μ_β	-1.437	$\ln t_m$	5.96	5.95
$\sigma_{b_1}^2$	0.504	$\ln t_f$	6.64	6.65
$\sigma_{b_2}^2$	0.323	$\text{sd}(\ln w_{m,1})$	0.60	0.61
σ_ϕ^2	0.586	$\text{sd}(\ln w_{m,2})$	0.55	0.55
σ_β^2	0.525	$\text{sd}(\ln h_m)$	0.27	0.34
σ_a^2	0.117	$\text{sd}(\ln h_f)$	0.41	0.51
ρ_{b_1,b_2}	0.271	$\text{sd}(\ln t_m)$	0.82	0.81
ρ_{ϕ_i,ϕ_j}	0.619	$\text{sd}(\ln t_f)$	0.66	0.71
ρ_{β_i,β_j}	0.923	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.46
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.761	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.37
m_λ	3.140×10^{-4}	corr_{l_m,l_f}	0.18	0.18
ζ	6.301×10^{-5}	corr_{t_m,t_f}	0.20	0.19
α	0.485	corr_{w_m,w_f}	0.39	0.38
σ	0.398	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.28

Notes: Exogenous parameters in calibration: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

bration are 7.69 and 7.49, respectively. And the log mean hours of housework by men and women are 5.95 and 6.65, respectively. Since households act as unitary decision-makers in our model, $\mu_\phi = 24.301$ directly affects the sum of non-leisure hours in a family. The preferences for home production ($\mu_\beta = -1.437$) further determine how non-leisure hours are divided into market hours and home hours. The gender asymmetry in market hours arises from Pareto weights and social norms ($\zeta = 6.301 \times 10^{-5}$). Pareto weights affect the gender gap in hours of working through two channels. On the one hand, a higher Pareto weight suggests lower labor force participation in comparative statistics. On the other hand, the Pareto weight is a realization of bargaining power given household characteristics. The relative wage between spouses is jointly determined by their working hours and abilities in the model. Though it cannot be directly shown in the model, lower working hours would lead to less wages, resulting in less bargaining power in allocation. The reshape parameter $m_\lambda = 3.140 \times 10^{-4}$ is calibrated to match the gender gap in working hours caused by these two forces. The gender asymmetry in housework hours will be further related to the share and substitution parameter in the CES home production function. The share parameter ($\alpha = 0.485$) captures a slight difference in female and male labor shares in total home output. The substitution parameter ($\sigma = 0.398$) implies that female and male efficiency units of household labor are imperfect substitutes so that men would need to devote time to housework.

The standard deviation of log male wages by occupation is matched by setting a higher variance in ability 1 than ability 2 ($\sigma^2_{b_1} = 0.504, \sigma^2_{b_2} = 0.323$). The mean differences in male wages across occupations are 46%, slightly lower than the data moment 48%. The correlation of abilities in the two occupations mainly influences the occupational wage gap through selection as suggested by a standard Roy model. The calibration yields a positive correlation between abilities ($\rho_{b_1,b_2} = 0.271$). Thus, a part of the wage gap across occupations is sourced from the selection of high-ability individuals into occupation 1. The model also slightly underestimates the wage gap between occupations of women (0.37 in the model, 0.42 in the data). It successfully captures the fact that the occupational wage gap of men is larger than that of women. The calibrated occupational-specific gender gaps in abilities ($\Delta\mu_{b_1} = 0.301, \Delta\mu_{b_2} = 0.014$) help to match this. The gender wage gap in the model (28%) closely matches the data. The magnitude of the gender gap in skills plays an important role in matching this asymmetry.

The model matches the correlation of leisure and home hours within households closely. The within-household correlation of leisure is 0.18 in both the model and the data, and the correlation of home hours are 0.19 in the model and 0.20 in the data. The correlation of wages within households is also closely matched with the data (0.38). Since intra-household interactions create a substitution effect within the household, the model requires a high correlation of tastes and abilities to match the positive correlations found in the data. These high correlations regarding tastes and skills can be explained by positive assortative matching in marriage markets.

The model fits the standard deviation of log home hours well. While $\sigma^2_\beta = 0.525$ and $\sigma^2_a = 0.117$ would be directly related to the magnitude of standard deviation, the gender difference in the variance of home hours is again matched by the share parameter and the substitution parameter ($\alpha = 0.485$ and $\sigma = 0.398$, respectively). The targeted moments that the model had issues with fitting relate to the standard deviation of log market hours. The model overestimates the variance of market hours for both men (0.34) and women (0.51). This may be due to the fact that in the model individuals are more flexible in choosing working hours compared to the real world. The intra-household interactions create dispersions in hours of working, which cannot be narrowed down enough by calibrating the variance ($\sigma^2_\phi = 0.619$) in tastes for leisure.[26]

[26]Further reducing σ^2_ϕ does not have a substantial effect on the variance of market hours.

6 Results & Analysis

The intuition behind our framework is that due to gender norms dictating women's housework hours and disproportionate rewards to hours in certain occupations (but not others), women who could have excelled in these nonlinear occupations may be discouraged from pursuing these careers and turn to ones that offer more flexibility. This mechanism causes a misallocation of talent across occupations but only if both gender norms and differences in temporal flexibility across occupations exist.

If all occupations have the same level of nonlinearity in wages, social norms would not distort the "attractiveness" of occupations for they all offer the same temporal (in)flexibility, and thus would not have a direct effect on talent allocation. And if there are no gender-specific time constraints, nonlinear pay schemes would not be a source of talent misallocation because agents would simply pursue careers they have the most comparative advantage in, given the wage schemes, thus we cannot reallocate people to achieve higher outputs. If there exists gender norms that distort female labor supply, there will be talent misallocation effects as long as there is heterogeneity in the degree of nonlinearity across occupations for there will be women who are hindered from pursuing their optimal careers. When there exist gender norms and the dispersion in nonlinearity across occupations is large, the misallocation effects would be magnified for in this case, women would not only be hindered by social norms from participating in the labor force but also strongly discouraged from pursuing nonlinear careers by its remuneration schemes.

In this section, we conduct counterfactual analyses to measure the effect of social norms on aggregate output and talent allocation. By removing social norms related to household divisions of labor ζ, gender differences in ability $\Delta\mu$, and setting different levels of nonlinearity one by one, we are able to distinguish between aggregate effects caused by different sources. We further conduct a policy experiment to see whether subsidizing home production can attenuate the effects of misallocation caused by social norms. At the end of this section, we conduct robustness checks of our results by changing the value of θ and $\bar{h}$.

6.1 Output Gains and Talent Misallocation

Overall, we find that gender differences in general have important effects on aggregate outputs. There are two sources of gender differences in our model: the difference in occupational abilities ($\Delta\mu$) and social norms (ζ). The ability differences in our model is a composite term that reflects gender differences not related to housework responsibilities. It could contain factors such as the gender gap in human capital accumulation or wage discrimination not related to hours worked. As the focus of our study lies in time-related gender differences, we will not analyze the effects of this term in detail. Rather, it represents a general gender difference in the economy that cannot be captured by ζ.

The results of our baseline counterfactual analysis are shown in Tables 4 and 5. Table 4 presents percentage changes in aggregate outputs and output per head while Table 5 illustrates the simulated hours and occupational share in different scenarios. Removing social norms alone increases the total market output by 6.14%; removing ability differences alone increases the total market output by 10.21%; and removing both norms and ability differences increase the total market output by 15.19%. The large gain in market output mainly comes from gains in women's market output in occupation 1, which can be further attributed to the increase in women's market hours and female talent reallocation from occupation 2 to occupation 1 as illustrated in Table 5. Removing ability differences and social norms reduces aggregate home output as a result of a decrease in home hours.[27]

The calibrated values of $\Delta\mu_1$ and $\Delta\mu_2$ suggest that women's mean ability is about 30% less than men's in occupation 1, but only 1.4% in occupation 2.[28] The large difference between the ability gaps lowers women's propensity of choosing occupation 1 because of comparative disadvantage. Table 5 (Columns (1) and (3)) shows that there exists a large degree of talent misallocation caused by uneven ability gaps in two occupations. When removing gender differences in both occupations, the effect of increasing women's ability in occupation 1 outweighs it in occupation 2, leading to a large increase in the share of female employment in occupation 1. The large talent reallocation effect further increases aggregate market output, mainly through increasing women's output in occupation 1. (Table 4, Column (2)).

Though a large proportion of output gains come from eliminating ability differences, social norms also generate considerable distortions regarding market output and talent allocation as shown in Column (1) of Table 4. Removing social norms women's market hours by around 11%. If there was no uneven division of social responsibilities, women would spend less time on home production

[27] We cannot identify the value of home production given the moments we have. Using the estimates we suggest when conducting policy experiments, total output increases by 4.76%, 8.89%, and 12.63% when we remove ζ, Δ_μ, and $\zeta\&\Delta\mu$, respectively. We interpret this effect size with caution, but it should be obvious that the gain in market output exceeds the loss in home output in any reasonable estimate of the home production value.

[28] Our paper does not aim to answer the question why $\Delta\mu_{b_1}$ is much larger than $\Delta\mu_{b_2}$. However, given that the educational gap has significantly narrowed in recent years, a possible explanation of this large ability difference we can offer is differences in on-the-job human capital accumulation. As occupation 1 features a greater nonlinearity, individuals' ability in occupation 1 may also be subject to this nonlinearity. Women cannot commit to this inflexibility due to social norms, thus they accumulate less human capital than men. In other words, there exist interaction effects between nonlinearities, social norms, and abilities. We leave this pathway for future explorations.

Table 4: Percentage Changes in Aggregate Output

	Adjustments		
	ζ	$\Delta\mu$	ζ & $\Delta\mu$
	(1)	(2)	(3)
Aggregate output			
Aggregate market output	6.14	10.21	15.19
Women's market output in occupation 1	13.65	64.43	68.93
Women's market output in occupation 2	7.80	-23.51	-17.28
Women's market output	10.96	32.59	37.55
Men's market output in occupation 1	2.19	-12.14	-4.89
Men's market output in occupation 2	4.82	4.80	3.71
Men's market output	2.84	-7.72	-2.71
Aggregate home output	-6.84	-2.22	-8.96
Output per head			
Women's market output in occupation 1	4.06	27.38	28.86
Women's market output in occupation 2	14.73	11.93	22.46
Men's market output in occupation 1	1.19	-7.96	-3.11
Men's market output in occupation 2	6.45	-1.55	0.92

Notes: baseline economy: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

and more time on market work. An increase in hours of working first directly increases the output. Further, under the nonlinear payment scheme (or mapping of efficiency units of labor), increasing hours of working results in a direct increase in productivity, leading to an increase in aggregate output. On the other hand, removing social norms also promote talent reallocation across occupations. To see why this is the case, first note that the increase of women's aggregate output in occupation 1 (13.65%) is larger than it in occupation 2 (7.80%). However, in terms of output per head, women's market output per head increases by 14.73% in occupation 2 but only by 4.06% in occupation 1 (Column (1), Table 4). This is due to an increase in the share of female employment in occupation 1 (from 0.40 to 0.44) as shown in Table 5. Those who are not relatively talented enough to choose occupation 1 might transfer from occupation 2 to occupation 1 after removing social norms. As more women choose to work in occupation 1, aggregate output increases by a significant proportion, but a negative selection effect constrains the increase in output per head.

To see this selection effect more clearly, we plot the distribution of relative abilities (ability 1 over ability 2) and occupational choices in Figure 7. The

Table 5: Changes in Labor Supply and Occupation

	Adjustments			
	No	ζ	$\Delta\mu$	ζ & $\Delta\mu$
	(1)	(2)	(3)	(4)
Occupation				
The share of female employment in occupation 1	0.40	0.44	0.58	0.60
The share of male employment in occupation 1	0.62	0.62	0.60	0.60
Hours				
Women's market hours	7.49	7.60	7.59	7.65
Women's home hours	6.65	6.43	6.48	6.28
Men's market hours	7.69	7.71	7.63	7.67
Men's home hours	5.95	6.06	6.12	6.21

Notes: baseline economy: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$. Hours are in logs.

figure shows that, in the region where the ratio of standardized relative skills ranges from 0.7 to 1.3, comparative advantage is not decisive. Intra-household interactions and hours of working also affect how women trade off between two occupations. If there were no social norms regarding women's market hours, the marginal utility gained from women's market hours would increase more in occupation 1 than in occupation 2, given differences in nonlinearities across occupations. Hence, many women with marginal relative abilities would switch from linear occupation to nonlinear occupation. Figure 7 clearly illustrates this point.

We then decompose the effect of social norms on women's aggregate output by dividing women into two groups. We calculate the output gains for those who do not change their occupation when social norms are removed and the output gains for those who change their occupation separately. We find that increasing market hours alone accounts for around 85 percent of the increase in women's market output, while talent reallocation accounts for the remaining 15 percent of the increase in women's market output. Hence, the additional talent misallocation effects introduced by the interaction of social norms and nonlinearities amplify the negative effects of social norms, resulting in larger output losses.

The analysis above has provided strong evidence of the interaction effects between social norms and nonlinearities. Note that the share of male employment in occupation 1 does not change, we expect that intra-household interactions should not be the cause of talent misallocation. We further set $\theta_1 = \theta_2$ to verify that talent misallocation happens because of the heterogeneity in wage structures.

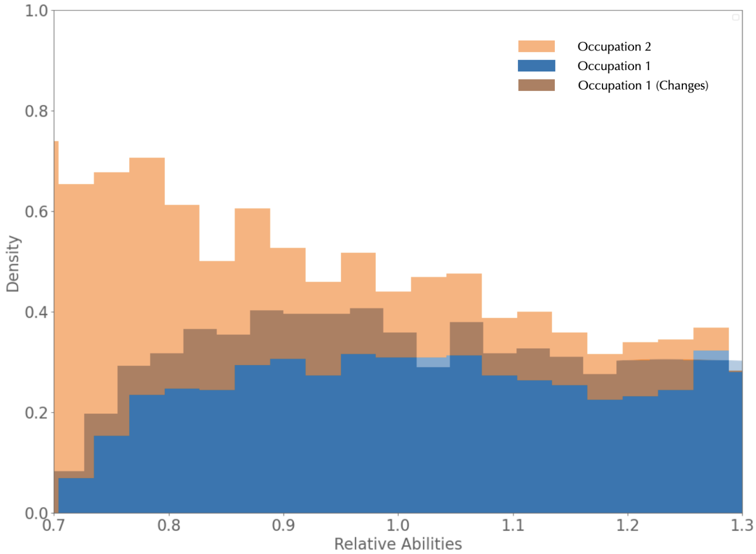

Figure 7: Relative Abilities and Occupation Choices (Female)

Notes: we standardize the ratio of abilities so that the ratio of mean abilities would be equal to 1. We only show ratios between 0.7 and 1.3 where talent reallocation across occupations happens. Figure 7 is generated from two simulations, thus the bin wide may vary.

Table 6 compares the effects of removing social norms in different nonlinear payment structures. We compare our baseline counterfactual results to two alternatives ($\theta_1 = \theta_2 = 0$, $\theta_1 = \theta_2 = 0.2$). The first two columns show the result in the baseline counterfactual again. Columns (2a) - (3b) show results for when there are no differences in nonlinearity across occupations. Working hours increase by similar proportions in all scenarios, suggesting similar effects of social norms on hours. Though removing social norms would still increase aggregate outputs by increasing women's market hours, it has no effect on talent reallocation across occupations. We conclude this because: 1) there is no improvement in the share of female employment in occupation 1; 2) women's market output per head increases more in occupation 1 than it in occupation 2.

To summarize, the results of our counterfactual analysis suggest that social norms (the uneven division of nonmarket responsibilities) have no effects on female occupation choices if occupations feature the same degree of nonlinearity. Talent misallocation happens because of interactions between social norms and different levels of nonlinearity across occupations. When one occupation features a greater nonlinearity compared to another, the occupational choice would be determined by both comparative advantage and hours of working. In the region where comparative advantage is not decisive, both intra-household allocation and social norms would affect occupational choices. The longer working hours you are able to commit to a job, the higher the propensity that you will choose the occupation that features a greater nonlinearity. Women with marginal talents who could have worked in the nonlinear occupation may change to the linear

Table 6: Effects with different nonlinearities

	Nonlinearities					
	$\theta_1 = 0.6, \theta_2 = 0.2$		$\theta_1 = 0, \theta_2 = 0$		$\theta_1 = 0.2, \theta_2 = 0.2$	
	Adjustments					
	No	ζ	No	ζ	No	ζ
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Output per head (percentage changes)						
Aggregate output	-	6.14	-	4.50	-	4.42
Women's market output in occupation 1	-	4.06	-	11.12	-	13.72
Women's market output in occupation 2	-	14.73	-	8.89	-	7.78
Occupation						
The share of female employment in occupation 1	0.40	0.44	0.40	0.40	0.40	0.40
The share of male employment in occupation 1	0.62	0.62	0.62	0.62	0.61	0.62
Hours						
Women's market hours	7.49	7.60	7.50	7.62	7.50	7.61
Women's home hours	6.65	6.43	6.66	6.40	6.65	6.41

Notes: $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$. Hours are in logs.

occupation because they are hindered by social norms from working long hours.

6.2 Policy Experiment

The counterfactual analysis suggests that talent misallocation may happen when social norms and differences in nonlinearity across occupations co-exist. Can such talent misallocation effects be attenuated by subsidizing home production? How about the cost of subsidizing? We perform a simple policy experiment regarding our baseline calibration in this section. We assume that the government would subsidize women's home hours directly. This can be understood as, for example, directly providing a certain amount of child care to each household. Since we cannot identify the value of home production through our model due to the lack of moments, we assume that wages in home production are about half of the average wages in occupation 2. This is consistent with what we observe from IPUMS CPS data, where the median wage of housekeeping and childcare workers is roughly a half of the weighted average wage in occupation 2.[29] Since we do not have a general equilibrium framework including a tax system to measure the costs and benefits exactly, our results are only partial effects and should be only treated as simple comparisons between direct gains and losses.

The results of the policy experiment are presented in Table 7. In general, subsidizing women's home hours have a positive effect on aggregate market output, mainly through increasing women's market output. Subsidizing home hours partly offset the negative effect caused by social norms, increasing women's market hours and share of employment in occupation 1. The increase in market output would exceed its cost if the government subsidizes more than 30% of women's home hours, which is around 230 hours per year in our data.

6.3 Robustness to Alternative Values of θ and $\bar{h}$

Since θ and $\bar{h}$ would affect optimal hours of work and intra-household interactions, we check the robustness of our results by assigning different values of θ and $\bar{h}$. We recalibrate parameters so that the model continues to fit the targeted moments, details are shown in Appendix C and D. Table 8 and Table 9 present the results of the robustness checks of θ and $\bar{h}$, respectively. Columns (1a) and (1b) again show the baseline result in both tables, while columns (2a)-(4b) show

[29] The median (real) hourly wage of childcare workers in our data is 4.46 USD and the median (real) hourly wage of maids and housekeeping workers is 4.33 USD. The weighted mean of hourly wages in occupation 2 is around 9.06 USD. We use the median instead of the mean for it better captures the amount the government would need to pay in order to provide these services. The mean wage of these occupations is much larger than the median for it includes a handful of workers in those occupations that receive much higher than average wages that drive up the mean. It is reasonable to assume that government-appointed housework services would be closer in price to the median than the mean.

Table 7: Effects of subsidizing home hours

	Subsidizing				
	0%	10%	20%	30%	40%
	(1)	(2)	(3)	(4)	(5)
Output (percentage changes)					
Womens' market output	-	3.78	6.92	7.25	11.63
Men's market output	-	-1.64	-2.84	-0.90	-0.91
Aggregate home output	-	5.26	4.23	8.03	8.38
Aggregate market output	-	0.53	1.13	2.43	4.24
Occupation					
The share of female employment in occupation 1	0.40	0.41	0.41	0.41	0.42
The share of male employment in occupation 1	0.62	0.61	0.60	0.60	0.61
Hours					
Women's market hours	7.49	7.52	7.55	7.57	7.58
Women's home hours	6.65	6.57	6.49	6.41	6.34
Cost (percentage of market output)	-	0.78	1.57	2.35	3.14

Notes: Baseline economy: $\theta_1 = 0.6, \theta_2 = 0.2, T = 5460$, $\bar{h} = 2600$, $\gamma = 4$. Hours are in logs.

results regarding different values of θ of $\bar{h}$.

The aggregate market output increases by 3.73% to 6.14%, varying with θ and $\bar{h}$, suggesting that uneven levels of household responsibilities cause a considerable amount of market output losses. The output gain again is associated with two factors: an increase in female labor hours and talent reallocation. Female labor hours increase by approximately 10% in all cases when we set $\zeta = 0$, resulting in a direct increase in productivity and output. More importantly, Table 8 and Table 9 again show that social norms cause talent misallocation across occupations when the two occupations feature different nonlinearities. The share of female employment in occupation 1 rises by 3 to 6 percent when we remove social norms. The changes in hours are similar. And in all cases, women's output per head increases more in occupation 2 than in occupation 1, while at the aggregate level, women's output increase in occupation 1 contributes more than in occupation 2. Collectively, these results suggest that our results are robust to different values of θ and $\bar{h}$.

Table 8: Robustness Check to θ

	Different values of θ							
	Baseline		$\theta_1 = 0.7, \theta_2 = 0.2$		$\theta_1 = 0.5, \theta_2 = 0.2$		$\theta_1 = 0.6, \theta_2 = 0$	
	Adjustments							
	No	ζ	No	ζ	No	ζ	No	ζ
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Output (percentage changes)								
Aggregate market output	-	6.14	-	4.96	-	5.73	-	3.73
Womens' market output	-	10.96	-	9.36	-	10.82	-	9.38
Women's market output in occupation 1	-	13.65	-	10.25	-	14.07	-	13.54
Women's market output in occupation 1 (per head)	-	4.06	-	1.63	-	5.71	-	1.10
Women's market output in occupation 2	-	7.80	-	8.26	-	7.27	-	3.21
Women's market output in occupation 2 (per head)	-	14.73	-	14.18	-	13.67	-	12.64
Occupation								
The share of female employment in occupation 1	0.40	0.44	0.39	0.43	0.41	0.45	0.40	0.46
The share of male employment in occupation 1	0.62	0.62	0.61	0.62	0.60	0.61	0.63	0.63
Hours								
Women's market hours	7.49	7.60	7.49	7.59	7.49	7.59	7.48	7.60
Women's home hours	6.65	6.43	6.65	6.44	6.66	6.42	6.67	6.44

Notes: $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$. Hours are in logs.

Table 9: Robustness Check to $\bar{h}$

	Different values of $\bar{h}$							
	Baseline		$\bar{h} = 2500$		$\bar{h} = 2700$		$\bar{h} = 2800$	
	Adjustments							
	No	ζ	No	ζ	No	ζ	No	ζ
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Output (percentage changes)								
Aggregate market output	-	6.14	-	5.82	-	5.90	-	4.63
Womens' market output	-	10.96	-	9.64	-	9.59	-	10.64
Women's market output in occupation 1	-	13.65	-	11.12	-	11.42	-	15.14
Women's market output in occupation 1 (per head)	-	4.06	-	2.50	-	3.97	-	5.26
Women's market output in occupation 2	-	7.80	-	7.94	-	7.33	-	5.50
Women's market output in occupation 2 (per head)	-	14.73	-	14.43	-	12.82	-	12.39
Occupation								
The share of female employment in occupation 1	0.40	0.44	0.41	0.45	0.41	0.44	0.39	0.43
The share of male employment in occupation 1	0.62	0.62	0.61	0.61	0.61	0.62	0.61	0.61
Hours								
Women's market hours	7.49	7.60	7.49	7.59	7.49	7.59	7.48	7.58
Women's home hours	6.65	6.43	6.65	6.43	6.65	6.44	6.67	6.44

Notes: $T = 5460$, $\theta_1 = 0.6$, $\theta_2 = 0.2$, $\gamma = 4$. Hours are in logs.

7 Conclusion

In this paper, we investigated and quantified the effects of gender differences on aggregate market ssoutputs using a static equilibrium model. We paid particular attention to the interaction between gender norms and temporal flexibility and found that it can have adverse effects on market outputs. Gender norms related to housework responsibilities not only directly constrain women's labor market availability but can also distort occupational choices when there exists heterogeneity in wage structures across occupations. A simple policy experiment using our framework shows that subsidies on women's housework hours can partly attenuate the negative effects of social norms.

Our study differentiates from existing work in the field in that we emphasize the role of social norms on the intensive margin and occupational sorting under nonlinear wages. We find that the negative effects of social norms would be magnified if the degree of nonlinearity differs across occupations because of an additional talent misallocation effect.

A natural extension to this paper would be to modify the model to a life-cycle framework to allow for analysis in a dynamic setting. The large differences in occupation-specific ability that could not be fully explored by our framework could also be of interest to future research. Incorporating additional dimensions such as educational attainment, marriage market, or on-the-job training into our model could also facilitate understanding of the complex mechanisms of gender-based talent misallocation. We leave these possibilities for future research.

A Calibration Method

We solve and calibrate our model using Python. The households' occupational choice and time allocation problem are solved by using Dual Annealing Method in Scipy which allows for global searching. The FOCs of the problem do not have an analytical solution, thus we need to solve the optimum numerically. The existence of multisolutions makes it difficult to get the optimal point by interpolating. The advantage of using Dual Annealing is its stability, but it also requires a longer computing time when solving the problem. We accelerate the solving process by applying multiprocessing, but it still takes a long time for each simulation. One simulation with 10000 households performed on a MacBook Pro (13-inch, M1, 2020, 8CPU) takes approximately 450 seconds to finish. The calibration is performed by minimizing the distance between simulated moments and data moments. We weight each moment equally for simplicity. For future extensions, we need to modify and improve the algorithm. One possible way is to use a discrete time allocation as suggested by Van Soest (1995), Blundell and Shephard (2012), and Gayle and Shephard (2019).

B Baseline Economy

Table 10: Baseline economy: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.62	7.77	5.76	5.16	0.27	0.78	0.61
Linear	0.38	7.54	6.21	4.70	0.40	0.77	0.55
Aggregate	1.00	7.69	5.95	4.93	0.34	0.81	0.62
Female							
Nonlinear	0.40	7.60	6.50	4.56	0.49	0.76	0.64
Linear	0.60	7.40	6.74	5.00	0.50	0.67	0.58
Aggregate	1.00	7.49	6.65	4.72	0.51	0.71	0.63

Table 11: Calibration of fixed Pareto weight λ

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	2.788	S^1_m	0.62	0.62
$\Delta\mu_{b_1}$	0.289	S^1_f	0.38	0.40
$\Delta\mu_{b_2}$	0.015	$\ln h_m$	7.68	7.71
μ_ϕ	24.213	$\ln h_f$	7.51	7.51
μ_β	-1.452	$\ln t_m$	5.96	5.97
$\sigma^2_{b_1}$	0.501	$\ln t_f$	6.64	6.66
$\sigma^2_{b_2}$	0.323	$\mathrm{sd}(\ln w_{m,1})$	0.60	0.60
σ^2_ϕ	0.303	$\mathrm{sd}(\ln w_{m,2})$	0.55	0.54
σ^2_β	0.555	$\mathrm{sd}(\ln h_m)$	0.27	0.31
σ^2_a	0.147	$\mathrm{sd}(\ln h_f)$	0.41	0.50
ρ_{b_1,b_2}	0.131	$\mathrm{sd}(\ln t_m)$	0.82	0.82
ρ_{ϕ_i,ϕ_j}	0.897	$\mathrm{sd}(\ln t_f)$	0.66	0.69
ρ_{β_i,β_j}	0.901	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.45
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.796	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.38
λ	0.368	corr_{l_m,l_f}	0.18	0.18
ζ	6.250×10^{-5}	corr_{t_m,t_f}	0.20	0.19
α	0.487	corr_{w_m,w_f}	0.39	0.39
σ	0.413	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.28

Notes: Exogenous parameters in calibration: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

C Sensitivity to θ

Table 12: Economy: $\theta_1 = 0.7$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.61	7.79	5.68	5.96	0.28	0.81	0.62
Linear	0.39	7.52	6.23	5.46	0.43	0.81	0.56
Aggregate	1.00	7.69	5.96	5.71	0.37	0.84	0.64
Female							
Nonlinear	0.39	7.64	6.46	5.32	0.51	0.82	0.67
Linear	0.61	7.36	6.77	5.79	0.52	0.68	0.60
Aggregate	1.00	7.49	6.65	5.49	0.52	0.74	0.65

Table 13: Calibration of $\theta_1 = 0.7, \theta_2 = 0.2$

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	3.550	S_m^1	0.62	0.61
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.39
$\Delta\mu_{b_2}$	0.016	$\ln h_m$	7.68	7.69
μ_ϕ	24.302	$\ln h_f$	7.51	7.49
μ_β	-1.437	$\ln t_m$	5.96	5.96
$\sigma_{b_1}^2$	0.492	$\ln t_f$	6.64	6.65
$\sigma_{b_2}^2$	0.303	$\mathrm{sd}(\ln w_{m,1})$	0.60	0.62
σ_ϕ^2	0.586	$\mathrm{sd}(\ln w_{m,2})$	0.55	0.56
σ_β^2	0.551	$\mathrm{sd}(\ln h_m)$	0.27	0.37
σ_a^2	0.117	$\mathrm{sd}(\ln h_f)$	0.41	0.52
ρ_{b_1,b_2}	0.271	$\mathrm{sd}(\ln t_m)$	0.82	0.84
ρ_{ϕ_i,ϕ_j}	0.650	$\mathrm{sd}(\ln t_f)$	0.66	0.74
ρ_{β_i,β_j}	0.923	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.50
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.821	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.43
m_λ	3.140×10^{-4}	corr_{l_m,l_f}	0.18	0.18
ζ	6.301×10^{-5}	corr_{t_m,t_f}	0.20	0.15
α	0.487	corr_{w_m,w_f}	0.39	0.35
σ	0.398	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.29

Notes: Exogenous parameters in calibration: $\theta_1 = 0.7$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

Table 14: Economy: $\theta_1 = 0.5$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.60	7.77	5.73	4.41	0.27	0.79	0.61
Linear	0.40	7.56	6.20	3.98	0.40	0.78	0.54
Aggregate	1.00	7.68	5.97	4.11	0.34	0.82	0.61
Female							
Nonlinear	0.41	7.55	6.57	3.83	0.48	0.76	0.63
Linear	0.59	7.43	6.71	4.26	0.47	0.68	0.56
Aggregate	1.00	7.49	6.66	3.96	0.48	0.71	0.60

Table 15: Calibration of $\theta_1 = 0.5, \theta_2 = 0.2$

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	2.051	S_m^1	0.62	0.60
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.41
$\Delta\mu_{b_2}$	0.016	$\ln h_m$	7.68	7.68
μ_ϕ	24.301	$\ln h_f$	7.51	7.49
μ_β	-1.447	$\ln t_m$	5.96	5.97
$\sigma_{b_1}^2$	0.492	$\ln t_f$	6.64	6.66
$\sigma_{b_2}^2$	0.303	$\mathrm{sd}(\ln w_{m,1})$	0.60	0.61
σ_ϕ^2	0.586	$\mathrm{sd}(\ln w_{m,2})$	0.55	0.54
σ_β^2	0.525	$\mathrm{sd}(\ln h_m)$	0.27	0.34
σ_a^2	0.117	$\mathrm{sd}(\ln h_f)$	0.41	0.48
ρ_{b_1,b_2}	0.271	$\mathrm{sd}(\ln t_m)$	0.82	0.80
ρ_{ϕ_i,ϕ_j}	0.619	$\mathrm{sd}(\ln t_f)$	0.66	0.71
ρ_{β_i,β_j}	0.921	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.42
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.805	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.29
m_λ	3.170×10^{-4}	corr_{l_m,l_f}	0.18	0.22
ζ	6.302×10^{-5}	corr_{t_m,t_f}	0.20	0.19
α	0.487	corr_{w_m,w_f}	0.39	0.43
σ	0.398	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.27

Notes: Exogenous parameters in calibration: $\theta_1 = 0.5$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

Table 16: Economy: $\theta_1 = 0.6$, $\theta_2 = 0$, $T = 5460$, $\bar{h} = 2500$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.63	7.78	5.73	5.15	0.21	0.81	0.60
Linear	0.37	7.50	6.28	2.70	0.37	0.81	0.53
Aggregate	1.00	7.70	5.99	4.96	0.32	0.84	0.61
Female							
Nonlinear	0.40	7.68	6.45	4.57	0.36	0.76	0.59
Linear	0.60	7.36	6.77	5.00	0.46	0.64	0.55
Aggregate	1.00	7.48	6.67	4.75	0.46	0.71	0.59

Table 17: Calibration of $\theta_1 = 0.6, \theta_2 = 0$

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	4.279	S_m^1	0.62	0.63
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.40
$\Delta\mu_{b_2}$	0.016	$\ln h_m$	7.68	7.70
μ_ϕ	24.200	$\ln h_f$	7.51	7.48
μ_β	-1.490	$\ln t_m$	5.96	5.99
$\sigma_{b_1}^2$	0.492	$\ln t_f$	6.64	6.67
$\sigma_{b_2}^2$	0.303	$\text{sd}(\ln w_{m,1})$	0.60	0.60
σ_ϕ^2	0.586	$\text{sd}(\ln w_{m,2})$	0.55	0.53
σ_β^2	0.548	$\text{sd}(\ln h_m)$	0.27	0.32
σ_a^2	0.117	$\text{sd}(\ln h_f)$	0.41	0.46
ρ_{b_1,b_2}	0.271	$\text{sd}(\ln t_m)$	0.82	0.84
ρ_{ϕ_i,ϕ_j}	0.642	$\text{sd}(\ln t_f)$	0.66	0.71
ρ_{β_i,β_j}	0.921	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.48
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.796	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.41
m_λ	3.050×10^{-4}	corr_{l_m,l_f}	0.18	0.20
ζ	6.090×10^{-5}	corr_{t_m,t_f}	0.20	0.19
α	0.493	corr_{w_m,w_f}	0.39	0.41
σ	0.398	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.27

Notes: Exogenous parameters in calibration: $\theta_1 = 0.6$, $\theta_2 = 0$, $T = 5460$, $\bar{h} = 2600$, $\gamma = 4$

D Sensitivity to $\bar{h}$

Table 18: Economy: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2500$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.61	7.76	5.80	5.14	0.25	0.80	0.61
Linear	0.39	7.55	6.21	4.70	0.40	0.77	0.54
Aggregate	1.00	7.68	5.98	4.90	0.34	0.82	0.61
Female							
Nonlinear	0.41	7.60	6.52	4.57	0.46	0.71	0.62
Linear	0.59	7.41	6.73	5.00	0.49	0.68	0.58
Aggregate	1.00	7.49	6.65	4.72	0.49	0.70	0.62

Table 19: Calibration of $\bar{h} = 2500$

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	2.797	S_m^1	0.62	0.61
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.41
$\Delta\mu_{b_2}$	0.016	$\ln h_m$	7.68	7.68
μ_ϕ	24.301	$\ln h_f$	7.51	7.49
μ_β	-1.437	$\ln t_m$	5.96	5.98
$\sigma^2_{b_1}$	0.492	$\ln t_f$	6.64	6.65
$\sigma^2_{b_2}$	0.303	$\text{sd}(\ln w_{m,1})$	0.60	0.61
σ^2_ϕ	0.586	$\text{sd}(\ln w_{m,2})$	0.55	0.54
σ^2_β	0.534	$\text{sd}(\ln h_m)$	0.27	0.34
σ^2_a	0.117	$\text{sd}(\ln h_f)$	0.41	0.49
ρ_{b_1,b_2}	0.271	$\text{sd}(\ln t_m)$	0.82	0.82
ρ_{ϕ_i,ϕ_j}	0.619	$\text{sd}(\ln t_f)$	0.66	0.70
ρ_{β_i,β_j}	0.921	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.43
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.811	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.33
m_λ	3.140×10^{-4}	corr_{l_m,l_f}	0.18	0.22
ζ	6.250×10^{-5}	corr_{t_m,t_f}	0.20	0.21
α	0.487	corr_{w_m,w_f}	0.39	0.40
σ	0.398	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.27

Notes: Exogenous parameters in calibration: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2500$, $\gamma = 4$

Table 20: Economy: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2700$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.61	7.78	5.76	5.16	0.28	0.81	0.62
Linear	0.39	7.55	6.21	4.68	0.41	0.81	0.55
Aggregate	1.00	7.69	5.96	4.93	0.36	0.84	0.63
Female							
Nonlinear	0.41	7.60	6.50	4.55	0.50	0.78	0.64
Linear	0.59	7.41	6.73	5.00	0.50	0.68	0.57
Aggregate	1.00	7.49	6.65	4.72	0.51	0.74	0.62

Table 21: Calibration of $\bar{h} = 2700$

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	2.799	S_m^1	0.62	0.61
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.41
$\Delta\mu_{b_2}$	0.016	$\ln h_m$	7.68	7.69
μ_ϕ	24.301	$\ln h_f$	7.51	7.49
μ_β	-1.437	$\ln t_m$	5.96	5.96
$\sigma_{b_1}^2$	0.492	$\ln t_f$	6.64	6.65
$\sigma_{b_2}^2$	0.303	$\mathrm{sd}(\ln w_{m,1})$	0.60	0.62
σ_ϕ^2	0.586	$\mathrm{sd}(\ln w_{m,2})$	0.55	0.55
σ_β^2	0.547	$\mathrm{sd}(\ln h_m)$	0.27	0.36
σ_a^2	0.117	$\mathrm{sd}(\ln h_f)$	0.41	0.51
ρ_{b_1,b_2}	0.271	$\mathrm{sd}(\ln t_m)$	0.82	0.84
ρ_{ϕ_i,ϕ_j}	0.650	$\mathrm{sd}(\ln t_f)$	0.66	0.74
ρ_{β_i,β_j}	0.930	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.49
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.808	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.38
m_λ	3.140×10^{-4}	corr_{l_m,l_f}	0.18	0.20
ζ	6.170×10^{-5}	corr_{t_m,t_f}	0.20	0.15
α	0.487	corr_{w_m,w_f}	0.39	0.35
σ	0.398	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.28

Notes: Exogenous parameters in calibration: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2700$, $\gamma = 4$

Table 22: Economy: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2800$, $\gamma = 4$

	Employment share	Log mean market hours	Log mean home hours	Log mean wages	Sd. of log market hours	Sd. of log home hours	Sd. of log wages
Male							
Nonlinear	0.61	7.78	5.76	5.18	0.27	0.82	0.62
Linear	0.39	7.54	6.24	4.71	0.41	0.81	0.56
Aggregate	1.00	7.69	5.98	4.91	0.36	0.85	0.63
Female							
Nonlinear	0.39	7.60	6.53	4.57	0.51	0.79	0.64
Linear	0.61	7.39	6.76	5.02	0.50	0.70	0.59
Aggregate	1.00	7.48	6.67	4.72	0.52	0.75	0.63

Table 23: Calibration of $\bar{h} = 2800$

Parameter	Value	Targeted Moments	Data	Model
μ_{b_2}	2.799	S_m^1	0.62	0.61
$\Delta\mu_{b_1}$	0.301	S_f^1	0.38	0.39
$\Delta\mu_{b_2}$	0.016	$\ln h_m$	7.68	7.69
μ_ϕ	24.301	$\ln h_f$	7.51	7.48
μ_β	-1.437	$\ln t_m$	5.96	5.98
$\sigma_{b_1}^2$	0.490	$\ln t_f$	6.64	6.67
$\sigma_{b_2}^2$	0.303	$\text{sd}(\ln w_{m,1})$	0.60	0.62
σ_ϕ^2	0.686	$\text{sd}(\ln w_{m,2})$	0.55	0.56
σ_β^2	0.601	$\text{sd}(\ln h_m)$	0.27	0.36
σ_a^2	0.119	$\text{sd}(\ln h_f)$	0.41	0.52
ρ_{b_1,b_2}	0.271	$\text{sd}(\ln t_m)$	0.82	0.85
ρ_{ϕ_i,ϕ_j}	0.671	$\text{sd}(\ln t_f)$	0.66	0.75
ρ_{β_i,β_j}	0.948	$\ln \bar{w}_{m,1} - \ln \bar{w}_{m,2}$	0.48	0.47
$\rho_{b_{i,1},b_{j,1}} = \rho_{b_{i,2},b_{j,2}}$	0.821	$\ln \bar{w}_{f,1} - \ln \bar{w}_{f,2}$	0.42	0.35
m_λ	3.140×10^{-4}	corr_{l_m,l_f}	0.18	0.20
ζ	6.130×10^{-5}	corr_{t_m,t_f}	0.20	0.20
α	0.487	corr_{w_m,w_f}	0.39	0.38
σ	0.380	$\ln \bar{w}_m - \ln \bar{w}_f$	0.29	0.31

Notes: Exogenous parameters in calibration: $\theta_1 = 0.6$, $\theta_2 = 0.2$, $T = 5460$, $\bar{h} = 2800$, $\gamma = 4$

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