Job Flexibility and Household Labor Supply: Understanding Gender Gaps and the Child Wage Penalty

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Abstract

This paper investigates how occupational flexibility affects the married couple's labor supply and the gender pay gap around childbirth. Using an event study specification and NLSY79, I document significant correlations between husband's and wife's occupational flexibility and the couple's labor adjustment around childbirth, based on the flexibility measure from Goldin (2014). Then I develop and estimate a dynamic household model with labor supply and occupational choice, where occupations are characterized by different wages and levels of flexibility. Using the estimated model, I find that exogenously switching occupational flexibility from low to high promotes wife's and husband's labor participation by 4 percentage points in the year of childbirth, respectively. Moreover, the same change in the husband's flexibility has a greater impact on the wife's labor adjustment than her own flexibility, increasing her labor participation and working hours by 10 and 7 percentage points, respectively. Finally, I evaluate the effects of counterfactual policies affecting occupational flexibility on household labor supply and the gender gap. When policies target wives only, they increase the wife's labor supply and reduce the gender pay gap in the long run by 8%. However, when both spouses are targeted, the positive effects on the wife's labor supply are weakened, and the gender pay gap expands in the long run.

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1 Introduction

The dramatic narrowing of gender employment and pay gaps experienced in the United States and other developed countries in the 1980s has since slowed, with persistent gender differences remaining[1]. In particular, the gender pay gap between married men and women is large and expands over the life cycle[2]. Recent studies also document that the career disruption after childbirth explains a substantial part of the unexplained gender difference in labor market outcomes[3]. Others find that the stricter time constraint that mothers face contributes to the gender pay gap[4]. These findings suggest that the incompatibility between market work and housework makes the households specialize more, and often women become the ones detached from the labor force. Then, it is natural to ask how to make the two tasks compatible and foster women's labor market attachment. Also, when the two tasks are harmonized, do we see a more balanced division of labor in the household?

The objectives of this paper are i) to investigate how men and women jointly choose their labor supply around childbirth given differences in "flexibility" across occupations, and ii) to evaluate how earnings inequality and labor market adjustments can be influenced by targeted policy interventions, affecting workplace flexibility after childbirth. WHAT IS FLEXIBILITY IN THIS PAPER WHOSE FLEXIBILITY DO I STUDY HOW FLEXIBILITY CAN PLAY A ROLE EXPLAIN

First, I construct a measure for occupational "flexibility" using O*NET database. Following Goldin (2014), I select five work activities and work context characteristics which are relevant for work place flexibility and time flexibility. A measure for the occupational flexibility is defined as the average of the five normalized characteristics. Based on this flexibility measure, I classify occupations into different flexibility groups. To verify whether the measure actually captures the workplace flexibility, I analyze if individuals with a young child use their work time and location differently when they hold a flexible occupation using American Time Use Survey. The result shows that individuals with a young child, when they hold a flexible occupation, they work less hours in total (ability to change working hours), they work more hours not in the typical working hours (ability

[1]See Blau and Kahn (2017), Cortés and Pan (2020) for the review

[2]Among others, Barth et al. (2021) documents the dynamics of gender earnings differentials along the life cycle by education level.

[3]See Angelov et al. (2016); Kleven et al. (2019a,b).

[4](Goldin, 2014; Cortés and Pan, 2019; Bertrand et al., 2010)

to shift working hours), and they are more likely to work from home (ability to change work location).

The occupational flexibility may affect maternal labor supply and earnings through two different channels. First, as pointed out by Goldin (2014) and Cortés and Pan (2019), women who are not able to work long hours earn less money per hour when the less flexible occupations nonlinearly compensate longer hours.[5] Second, when husbands work in occupations with less flexibility, then households may find it optimal to specialize more and unevenly split their labor supply among the spouses. In particular, women are more likely to detach from the labor market and/or reduce their working hours even further after childbirth, resulting in lower labor earnings after childbirth.

[REVISION NEEDED AFTER THIS POINT.]

I develop and estimate a joint household model to control for selection into occupations and hours worked. With the estimated model, I quantify the effect of job flexibility on household labor supply by comparing the baseline outcome with the counterfactual outcome where convexities in earnings are removed. Importantly, my model can provide a cross-elasticity of the husband's job flexibility on the wife's labor supply and vice versa. I further investigate the impacts of different policy instruments on household labor supply and the child penalty under heterogeneous responsiveness of husbands and wives. For example, I evaluate the expansion of paid parental leave, assignment of a "daddy quota" in paid parental leave, and tax policies mitigating convexities in after-tax earnings.

Related Literature

Contribution to the literature

One of the main contributions of this paper is to examine how the husband's job characteristics contribute to the child penalty and the overall gender pay gap. Previous studies have focused on the effects of the wife's own job characteristics, whereas the husband's side is largely unexplored (Wiswall and Zafar, 2017; Adda et al., 2017; Mas and Pallais, 2017; Hotz et al., 2017; Xiao, 2019). I show that there exists an important heterogeneity

[5] Relatedly, jobs with higher flexibility tend to offer lower wages per hour (Wiswall and Zafar, 2017; Adda et al., 2017).

across households in the husband's responsiveness in working hours to the event of childbirth. Further, I quantify to what extent the flexibility of both the husband's and wife's jobs influence their labor supply adjustments.

I develop a novel joint household framework that can be used to quantify the effects of programs incentivizing husbands to engage more in childcare and wives to remain active in the labor market. There is recent literature investigating the effects of the expansion of paid parental leave and the assignment of the father's quota on the labor supply of mothers and fathers (Ekberg et al., 2013; Patnaik, 2019; Byker, 2016). However, the empirical evidence is scarce in the U.S. which is the only developed country that does not have national-level paid leave for the new parents. This paper aims to provide an estimate of the effect of the expanded paid parental leave policies in the U.S. labor market.

The rest of the paper is organized as follows. Section 2 explains the data. Section 3 documents empirical facts describing household labor adjustment after childbirth by different job flexibility levels and important trade-off between job flexibility and earnings. Section 4 develops a joint household model. Section 5 discusses estimation and results. Section 6 present and discuss counterfactual policies. Section 7 concludes.

2 Data

2.1 NLSY79: A Household Panel

To study how households change their occupations and time allocations around childbirth, I need to track both spouses' labor supply and occupations pre- and post-birth periods. Also, to see whether the labor adjustments in the year of birth have long-term consequences on earnings and wages, I need to track them for a long period after the birth. National Longitudinal Survey of Youth 1979 (NLSY79) is one of a few data sources in the US, which allows me to track both spouses' labor market characteristics for a long period. The NLSY79 has followed the nationally representative sample of youth since 1979. Also, since the data sampled the youth in 1979, most individuals in the sample had their first childbirth observed during the sample period. If the youth gets married, the data also collects detailed information about their spouses, including their occupations and wages[6].

[6]Unfortunately, more recent NLSY data (NLSY97) do not provide spouses' occupation anymore.

I restrict the sample to the married couples with a wife's age between 19 and 45 for high school graduates and some college or between 24 and 45 for college graduates or above. I exclude the periods when any of the spouses is in school. As individuals who dropped from high schools have significantly different child-bearing patterns and labor market outcomes, I exclude these individuals from the sample. Additionally, my analysis is abstract from any dissolution of families. I exclude the period after any divorce, assuming the divorce as a random shock and households who would experience divorces in the future behave similarly to households who do not experience any divorce. Lastly, I exclude households with any self-employment income observed in the sample period. The flexibility in self-employment jobs can be conceptually different from the flexibility in employer-employed jobs. Also, households with one or more spouses self-selects into self-employment can be substantially different in their time allocation around childbirth. As a result of the sample selection criteria, I have 89837 household-year observations with 5642 unique household observations. On average, each household is observed for 15 years[7].

2.2 O*NET: Measure of Occupational Time Flexibility

As Goldin (2014) pointed out, occupational flexibility is "a complicated, multidimensional concept." It is hard to measure in nature, and one may think of every different way of constructing a measure of it. To avoid an arbitrary choice in numerous dimensions, I closely follow Goldin (2014) and use the same measure of flexibility used in her paper. This gives additional benefits to gauge the occupational flexibility in this paper in comparison to the occupational flexibility described in Goldin (2014). I use a much larger set of occupations, including lower-paying occupations, compared to the occupations in Goldin (2014). Indeed the measure well extrapolates and nicely captures the flexibility of these out-of-sample occupations in the original paper.

An occupation-specific flexibility measure is constructed as the average of five normalized O*NET characteristics[8]. These characteristics are "Time pressure", "Contact with others", "Establishing and maintaining interpersonal relationships", "Structured vs. un-

[7] The years may not be continuous, as the NLSY79 changed their frequency from annual to biennial since 1997.

[8] The O*NET database provides detailed occupational information, including work activities and work context, which are relevant to understanding occupational flexibility. Data is collected from a statistically random sample of workers who worked in the targeted occupations.

Table 1: Occupations ranked by the flexibility measure

Low Flexibility	High Flexibility
Chief executives	Biological Scientists
Producers and directors	Telephone operators
Financial managers	Musicians
Licensed practical and licensed vocational nurses	Teachers and instructors
Physicians and surgeons	Computer programmers

structured work", and "Freedom to make decisions."[9,10] Each characteristic is normalized with a mean of 0 and a standard deviation of 1 within a set of occupations in NLSY79[11]. I use O*NET responses sourced by the incumbents. Then the flexibility measure is merged into other household datasets using a crosswalk between the Standard Occupational Classification system and Census occupational codes[12] and calendar years. I use multiple versions of O*NET Databases which have evolved over time. For the crosswalk across different years of Census occupational codes, I use the harmonized occupation classification by Autor and Dorn (2013).

Table 1 shows the list of occupations sorted by the flexibility measure. Occupations such as chief executives and financial managers are among the least "flexible" occupations, whereas computer programmers and musicians are among the most "flexible" occupations. Although Goldin (2014) focuses on the flexibility of highly-educated workers, the measure also applies to lower-educated workers. Occupations held by highly-educated workers are generally less flexible; there is a fair amount of heterogeneity in flexibility conditional on education level. Appendix A documents more summary statistics of the flexibility measure sorted by workers' observable characteristics.

2.3 ATUS: Describing the Flexibility Measure

To better understand which dimensions of flexibility are captured in the measure of flexibility, I investigate if individuals with high flexibility scores utilize their time differently.

[9] See Goldin (2014) for an explanation of how each characteristic is related to time flexibility.

[10] For robustness check, I add/remove some other characteristics that are closely related to time flexibility, but most of results are robust to these variations.

[11] This potentially gives different scales from Goldin (2014), but this process would not change the rank between occupations

[12] Some Census occupations are matched to multiple O*NET SOC codes. In this case, I use an average flexibility score from all matched O*NET SOC codes.

In particular, I select individuals with a young child from the American Time Use Survey(ATUS) to see if the followings are different for people working in more flexible occupations: 1) total working hours, 2) hours shifts within a day, and 3) working locations.13Table 3 summarizes the results. After controlling for various individual characteristics including age, education, race, and gender, individuals with a young child and with more"flexibility" in their occupation based on the flexibility measure tend to:

1. Work fewer hours per week (*ability to change working hours*).
2. Be more likely to work in hours, not in typical working hours (*ability to shift working hours within a day*).
3. Be more likely to work from home in the intensive margin (*ability to change their work location*).

In column (1), it is shown that the one standard deviation increase in the flexibility score is associated with about 1.7 hours lower working hours per week. In column (2), the same one standard deviation increase in flexibility gives a 6.5 percentage point increase in the proportion of working hours, not in typical 9am-to-6pm working hours. As work shift typically depends on the total working hours, I also control for the total working hours per week. Lastly, in columns (3) and (4), I present the relationship between flexibility and work-from-home (WFH) utilization. In column (3), the relationship is not significant. This is because, for some occupations, the WFH arrangement is not actually an option. For example, for biological scientists, although the occupation may give flexible arrangements in terms of their time allocations, most of their tasks cannot be done at home. In column (4), I restrict the sample to individuals working in occupations with any work done at home and estimate the relationship between the flexibility and the intensive margin utilization of the WFH option. In the intensive margin, one standard deviation increase in flexibility score gives about 8.8 percentage point increase in the proportion of hours worked from home.

The result shown in the section describes the different dimensions of flexibility incorporated in the flexibility measure. But the scope may not be limited to these dimensions, and other dimensions are also relevant for the time allocation of the parents. The simplifying assumption of using uni-dimensional flexibility measure is these latent dimensions of flexibility are correlated and captured in this uni-dimensional flexibility to some degree. In the model, all the other dimensions of flexibility except the ability to change total working hours will be lumped, and they enter through a non-pecuniary benefit of holding a flexible occupation.

Table 2: Occupations ranked by the flexibility measure

	Working Hrs	Prop Hrs Not 9To6	Prop Hrs WFH	
	(1)	(2)	(3)	(4)
Flexibility Score	-1.717^{***}	0.065^{***}	0.002	0.088^{***}
	(0.351)	(0.007)	(0.008)	(0.026)
Ind. Char.	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Daily Working Hours		YES	YES	YES
Any WFH				YES
Observations	3,415	3,415	3,415	785

3 Empirical Facts

When the first childbirth happens, married couples adjust their time use significantly. Typically, husbands tend to work about the same hours or a little longer, if anything changes, whereas wives tend to quit their work or reduce their working hours significantly, at least temporarily (Angelov et al., 2016; Kleven et al., 2019a,b). In this section, I document interesting empirical facts about the relationship between occupational flexibility and labor supply decisions of the married couple around their first childbirth. Using an event study approach similar to Kleven et al. (2019a,b), I show that the labor adjustments around childbirth significantly differ across households with different occupational flexibilities.

Specifically, I focus on 1) the effects of own flexibility and 2) the effects of spousal flexibility measured in one year before the first childbirth on household labor adjustment after the birth. Then I also investigate the effects of own and spousal flexibility on wife's earnings and wages to measure the heterogeneity in child wage penalties across different flexibilities. First, I start from describing the specification of the event study used in this section.

3.1 Specification for Event Study

The specification for the regression is based on the specification used in Kleven et al. (2019b) with minor divergences from it. For each household i, with outcome variable y working in flexibility group g at event time t, I regress the outcome variable y_{itg} on the event time dummies except for the reference period (-1) and a set of control variables. The control variables include calendar year fixed effects, ages and education levels of both spouses, and average earnings in the pre-birth periods of both spouses.

I define the "event time" as the year since the first childbirth of the household. And the outcome of interest y_{itg} includes the wife's hours of work, work status, earnings, and wages. The flexibility group g can have four values depending on husband's and wife's occupational flexibility group based on occupations a year before the first childbirth: $g \in \{(H, H), (H, L), (L, H), (L, L)\}$. Specifically, the regression model can be written as follows:

$$y_{itg} = \sum_{\tau \neq -1} \alpha(g)_\tau \mathbb{I}(\tau = t) + f_g(Controls) + \nu_{itg} \tag{1}$$

Parameters on the event time dummies, $\alpha(g)_\tau$, can be interpreted as the changes in the mean value of the outcome y at event time τ relative to the year before birth for the flexibility group g. The non-parametric function f_g includes age dummies for husbands and wives, calendar year dummies, and college graduate dummies for both spouses together with their interaction term. The key difference of this specification compared to Kleven et al. (2019b) is that here the parameters $\alpha(g)_\tau$ is the changes in the outcome relative to the reference period; whereas Kleven et al. (2019b) converted it as difference in y relative to the counterfactual outcome at event time τ. Samples are selected to be households in which both spouses worked a year before the childbirth.

3.2 Women's Labor Adjustment By Men's Occupational Flexibility

First, I study how the husband's occupational flexibility is associated with the wife's intensive-margin labor supply after the first childbirth. Thus in this subsection, the relevant outcome variable is the log of the wife's working hours.

Figure 1 shows the results. Different panels show the households with different wives' occupational flexibilities. On the left-side panel, households with wives working in high flexibility occupations are presented, and on the right-side panel, households with wives working in less flexible occupations are presented. With different colors, I show the different husband's occupational flexibilities.

First, conditional on the husband's flexibility, women with high flexibility restore their pre-birth period working hours 2-3 years after the birth.

Second, for the wives who are working in less flexible occupations, women whose husband has low flexibility reduce their working hours more in the year of birth and restore working hours more slowly after the birth.

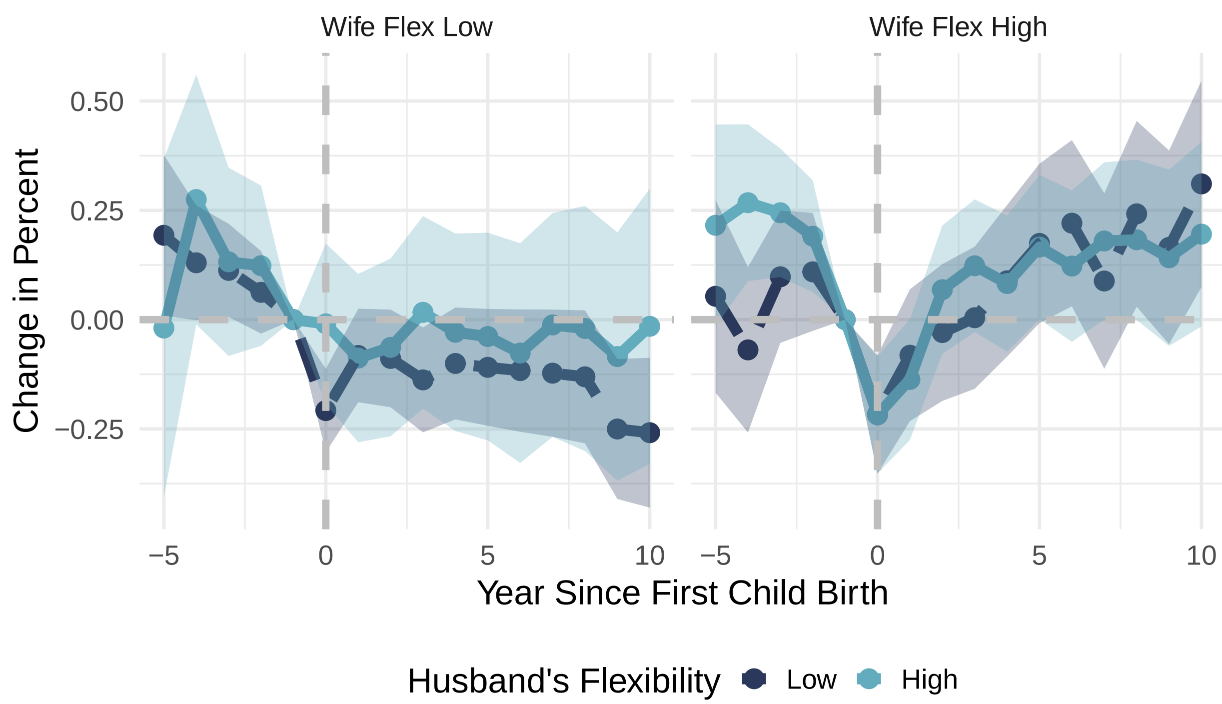

Figure 1: Changes in Wife's Working Hours Conditional On Working

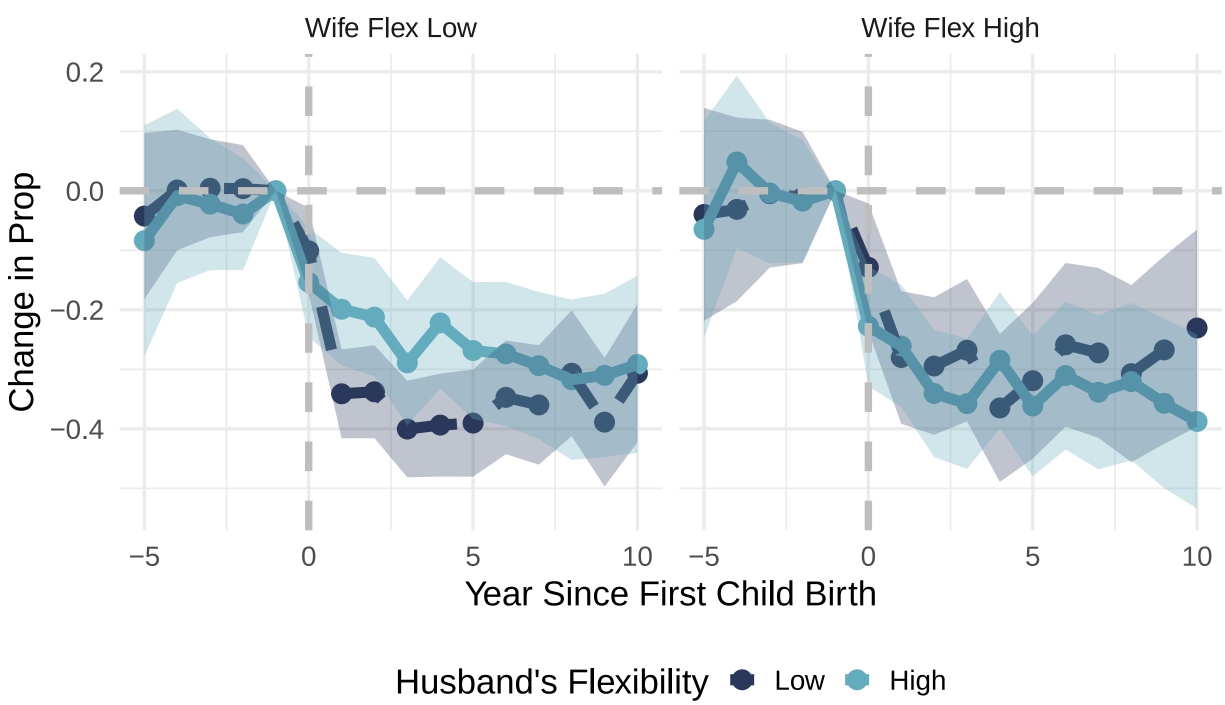

Figure 2: Change in Wife's Labor Participation Rates

3.3 Women's Labor Market Outcomes By Men's Occupational Flexibility

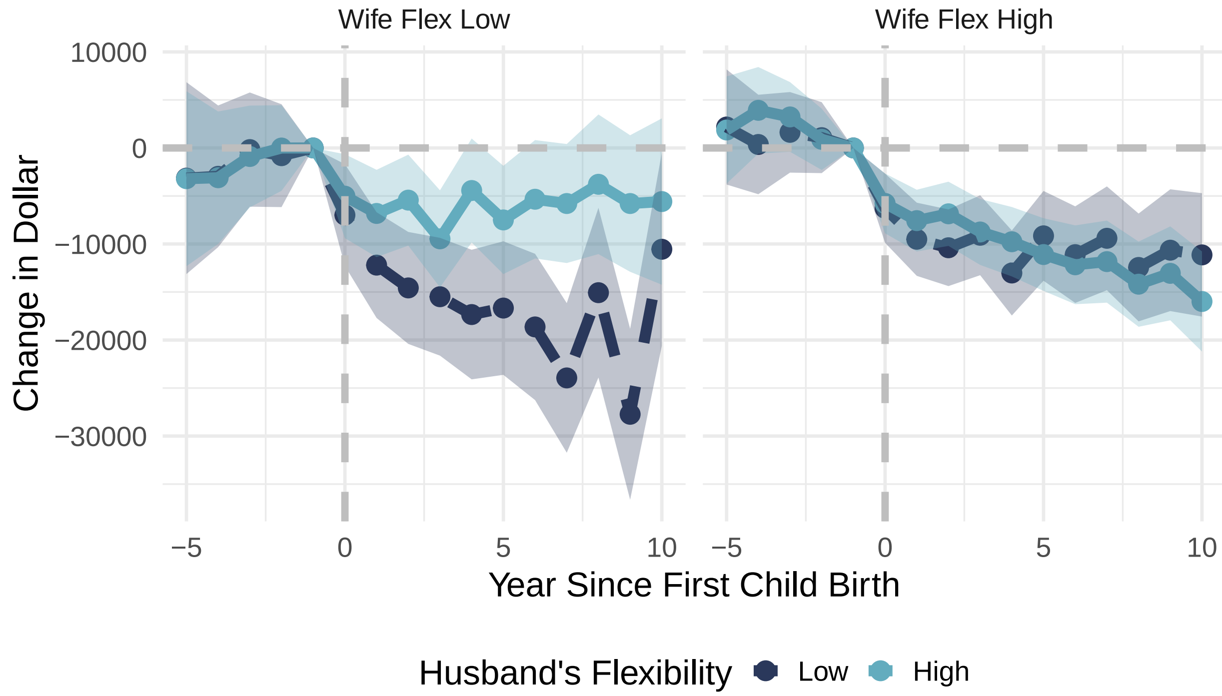

Figure 3: Change in Wife's Annual Earnings

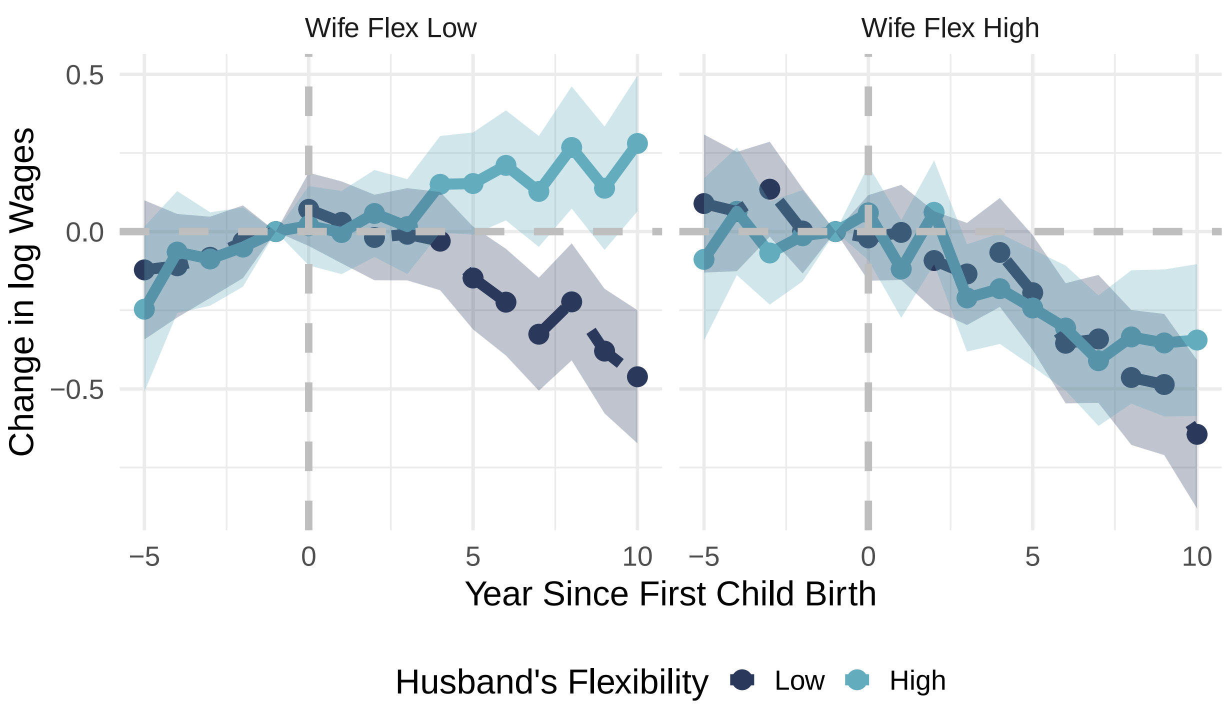

Figure 4: Change in Wife's Hourly Wages

3.4 Men's Labor Adjustment By Men's Occupational Flexibility

Table 3: Husband's Labor Adjustment From -1 to 0

Compared to (L, L)	Change in Prop (1)	Change in Hours (2)
$Flex_{Hus} = H, Flex_{Wif} = L$	-0.055	-166.072^{**}
	(0.075)	(89.445)
$Flex_{Hus} = L, Flex_{Wif} = H$	0.039	-49.130
	(0.073)	(87.152)
$Flex_{Hus} = H, Flex_{Wif} = H$	0.043	237.756^{*}
	(0.109)	(130.784)
Controls		
Age for both	X	X
Education for both	X	X
Year FE	X	X
Observations	610	610
R^2	0.158	0.188

Note: Changes between t = -1 (a year before the first birth) and t = 0 (the year of the first birth)

3.5 Occupational Flexibility and Earnings

4 A Dynamic Household Labor Supply and Occupational Choice

This section develops a dynamic discrete choice model of households with occupational choice and labor supply. The objective of this model can be summarized in three points. The first objective is to identify and estimate the model parameters governing households behavior around childbirth. The model provides a framework to understand the mechanisms generating strong interrelationships between husband's and wife's labor supply and occupational choice shown in the reduced form evidence in earlier sections. With the estimated model, I am able to evaluate counterfactual policies affecting household labor adjustment, assuming that these mechanisms do not change under the counterfactual policies.

Second, the model aims to relieve concerns about the identification problem arising from the endogenous occupational choice. This is particularly important if one might be interested in a policy effect on household labor supply as the policy would change households sorting into occupations. Sorting into the initial occupation at age 19 or 24 will be assumed to be random, and the subsequent occupational choices are modeled as endogenous choices of the household, thus can be fully controlled. I validate the assumption on the initial occupation in Appendix **??**.

Third, the model framework helps to disentangle the effects of flexibility from other confounding effects. In particular, the relationship between the flexibility and labor supply documented in the previous section might be interpreted as income effects. When the husband works in the inflexible occupation, it is shown that the wife drops from the labor force more, and the husband increases his hours worked. However, with the reduced-form exercise alone, I cannot distinguish if the observed relationship is the effect of flexibility or the effect of income. The trade-off between wages and flexibility hinders the identification of these confounding effects. With the estimated model, the effect from the flexibility margin can be separately evaluated by fixing income level in the model and changing only the flexibility margins.

In the model, each household has a unitary preference, and the time is discrete and finite. Occupations are characterized by different wage offers and flexibility. Each spouse gets a job offer from each occupation in every period. In every period, a household jointly chooses how much labor hours to supply in the labor market for each spouse and which occupation to work in for the next period. It is assumed that changing occupation is costly, and the cost is symmetric across any occupational changes. Human capitals are general, and households can accumulate them by working, and the rates of return to work potentially differ when they work in part-time positions. Fertility is assumed to be exogenous in the model. The probability of having a new child depends on the wife's age and both spouses' education levels.

Importantly, flexibility is modeled through two channels as 1) a non-pecuniary benefit from holding a flexible occupation and 2) occupation-specific part-time wage discount rates. Household starts with initial occupations, initial levels of human capital, and education levels. It is assumed that the schooling choices are completed before the wife's age 25 (for college graduates) or 19 (for high school graduates), and the education levels are fixed at this initial level throughout their life cycle.[13]

[13] In the data implementation, I only include individuals whose education level does not change after the starting age of 25 or 19.

Here, I present the household model in a recursive format. Each component of the model is described in detail in the subsequent subsections.

Value Function

In every period $t = 1, 2, ..., T$, household i with spouse $j = m, w$ solves the following optimization problem given the state variables, $\Omega_{it} = \{\vec{o}_{it}, \vec{E}_i, \vec{X}_{it}, \vec{\eta}_{it}, \vec{\varepsilon}_{it}, n_{it}\}$. The notations used in the model are summarised in Table 4.

$$V_t(\Omega_{it}) = \max_{\vec{h}_{it}, \vec{o}_{it+1}} u(\Omega_{it}, \vec{h}_{it}, \vec{o}_{it+1}) + \beta \mathbb{E}\left[V_{t+1}(\Omega_{it+1}) | \Omega_{it}, \vec{h}_{it}, \vec{o}_{it+1}\right]$$
$$s.t. \quad c_{it} + K(n_{it}, \vec{E}_i, \vec{h}_{it}) = \sum_j h_{ijt} w_{ijt}(\Omega_{it}) + y_{it}(\vec{E}_i)$$

Notation	Explanation	Notation	Explanation
$\vec{h}_{it} = [h_{imt}, h_{iwt}]$	Hours worked	$\vec{o}_{it} = [o_{imt}, o_{iwt}]$	Occupations
$\vec{E}_i = [E_{im}, E_{iw}]$	Education levels	$\vec{X}_{it} = [X_{imt}, X_{iwt}]$	Human capitals
$\vec{\eta}_{it} = [\eta_{imt}, \eta_{iwt}]$	Wage shocks	$\vec{\varepsilon}_{it}$	Choice-specific preference shocks
n_{it}	Age of the youngest child	$K(\cdot)$	Childcare cost
$y_{it}(\cdot)$	non-labor income		

Table 4: Notations in the Model

4.1 Occupation Choice and Labor Supply

There are N occupations in the model and M discrete choices for hours of work. When either of the spouses switches his/her occupation, the new occupation starts from the next period, and households are subject to switching costs, which are modeled as fixed utility costs. It is assumed that individuals choose the occupations for the next period and take the occupation for the current period as given when they make labor supply decisions. This timing assumption isolates the effects of the current wage shock on the choices of working hours only.

Labor supply can be one of the discrete working hours categories, $h_{ijt} \in \{0, h_1, h_2, ..., h_M\}$, where $h_l < \bar{H}$ and $\bar{H}$ is the total time endowment in a given period t. When individuals work 0 hours, i.e., not working, the total time endowment goes to leisure or non-working hours. In the model, leisure and non-working hours are indistinguishable, and I use the two terminologies interchangeably.[14] There are $N^2 * M^2$ mutually exclusive alternatives available to households, and households receive alternative-specific preference shocks drawn from Gumbel distributions. There is no non-voluntary layoff in the model, and temporal leaves with a job and non-working are treated identically.

4.2 Occupational Flexibility and Wage Structures

In order to capture the trade-off between occupational flexibility and compensation when choosing occupations, I model wage equations that differ by occupation. Specifically, different occupations offer different (1) baseline wages $\left(\beta_{0j}(o)\right)$, (2) wage premiums for college graduates $\left(\beta_{1j}(o)\right)$, and (3) returns to human capital $\left(\beta_{2j}(o), \beta_{3j}(o)\right)$. When individuals work in full-time positions, the wages are determined by an occupation-specific wage function, which gives the level difference in wages across occupations. Individuals are subject to idiosyncratic wage shocks, $\eta_{it} = (\eta_{imt}, \eta_{iwt})'$, which are independently and identically distributed across periods following a bivariate normal distribution with mean 0 and variance-covariance matrix Σ.

$$\textit{(Full-time wages)} \quad log(\tilde{w}_{ijt}) = \beta_{0j}(o_{ijt}) + \beta_{1j}(o_{ijt})E_{ij} + \beta_{2j}(o_{ijt})X_{ijt} + \beta_{3j}(o_{ijt})(X_{ijt})^2 + \eta_{ijt} \tag{2}$$

$$\eta_{it} \overset{iid}{\sim} N(0, \Sigma) \tag{3}$$

Importantly, the different dimensions of the flexibility are modeled in two different ways. First, the flexibility in changing total working hours year-to-year is captured through a gender-occupation-specific part-time wage discount function, $g_j(o, h)$, which discount full-time wages depending on the total hours of work. For example, if an occupation does not tolerate time flexibility, i.e., reducing working hours is heavily penalized, then the part-time hourly wage would be lower than the full-time hourly wage conditional on the education and human capital. Without loss of generality, I assume that h_M is the "full-time" working hours, and all other options, $\{h_1, h_2, ..., h_{M-1}\}$, are treated as "part-time" working hours. Notably, as I do not impose any restriction on $g_j(.)$, the "discount" rates can be estimated as negative numbers for some working hour options and for some

[14] In the implementation, I set the number of occupations as two, the number of hours worked as three, and the total time endowment as 16 hours per day (= 5840 hours per year.

occupations.

$$\textit{(Part-time wages)} \quad w_{ijt}(X_{ijt}, E_{ij}, o_{ijt}, h_{ijt}, \eta_{ijt}) = g_j(o_{ijt}, h_{ijt}) * \tilde{w}_j(X_{ijt}, E_{ij}, o_{ijt}, \eta_{ijt}) \tag{4}$$

Second, the flexibility in other dimensions, including changing work location or changing work shift, are lumped and modeled as the non-pecuniary benefit of holding a more flexible occupation. Utilizing these other dimensions of flexibility does not necessarily change the total working hours, and usually, they are harder to observe in the data without detailed information on activity-level time and location. Thus, I take a less structural approach to model these types of flexibility by adding a non-pecuniary benefit in the utility specification. Also, I assume that the non-pecuniary benefit is separable from any other terms in the utility specification. In addition, individuals who face increased childcare needs due to a newborn child may utilize these dimensions of flexibility more by changing work shifts or work locations. Thus, I allow the utility from the non-pecuniary benefit to depend on whether the household has a young child or not.

$$\textit{(Non-pecuniary benefit)} \qquad \alpha_j(n_{it})\mathbb{I}(o_{ijt} = o_h)\mathbb{I}(h_{ijt} \neq 0) \tag{5}$$

4.3 Human Capital Accumulation

In the model, human capital is general, and it accumulates depending on the total hours worked in a given period. The next period human capital X_{ijt+1} for spouse j is a function of the current human capital level X_{ijt} and current period's labor supply h_{ijt} relative to the maximum possible labor supply H_M. Thus, when a spouse j working in a full-time position, $h_j = h_M$, he/she will accumulate one unit of human capital in the next period. However, when the spouse works in one of the part-time options, the gender-specific parameter $\rho_j > 0$ governs the rate of return of additional hours of work to the human capital. I assume that there is no human capital depreciation when individuals are not working.

$$X_{ijt+1} = X_{ijt} + \left(\frac{h_{ijt}}{h_M}\right)^{\rho_j} \tag{6}$$

4.4 Fertility Shocks, Childcare, and Non-labor income

Fertility is an exogenous shock where its probability depends on the wife's age and both spouses' education level. This assumes that fertility shocks are random conditional on the education levels and wife's ages.[15] When there is a young child present in the household, the value of non-working hours changes for both spouses. In particular, when the age of the youngest child in the household (n_{it}) is less than 5, the value of leisure, γ_j for spouse j increases or decreases by $\bar{\gamma}_j$. If the estimated terms are positive, they motivate households to spend more time at home with their children.

$$\gamma_j(n_{it}) = \begin{cases} \gamma_j + \bar{\gamma}_j & if \quad 0 \leq n_{it} < 5 \\ \gamma_j & if \quad n_{it} \geq 5 \text{ or no child} \end{cases} \tag{7}$$

Households need to pay a fixed amount of childcare cost, $K(n_{it}, h_{imt}, h_{iwt})$, which depends on the age of the youngest child and the labor supply of both spouses. These costs are computed outside of the model using PSID 1980-2010. The estimated costs reflect that when both spouses are working, the household needs to pay higher child care costs. Also, conditional on one spouse's work status, working in a full-time position requires higher child care costs. There is no saving allowed in this model. Instead, there is an exogenous non-labor income stream known to the household, $y_{it}(\cdot)$, as a function of both spouses' education levels.

4.5 Utility Specification

The utility can be separated into three parts: 1) utilities from consumption and non-working hours, 2) utilities from non-pecuniary benefits and occupation switching costs, and 3) choice-specific shocks.

I use log utilities for the consumption and non-working hours, and utilities from spouses' non-working hours are separable in the utility specification. Utilities from the non-pecuniary benefit from the high flexibility occupation are specified as Equation 5. And the switching costs are assumed to be in utils, and they are gender-specific but symmetric across any occupational changes. The choice-specific preference shocks, ε_{it} follow a Gumbel distribution, and the scale parameter is normalized to identify all the other

[15]In the data, there's no substantial differences in fertility rates across different initial occupations.

parameters in the utility specification. Future utilities are discounted by the discount parameter β, which is assumed to be fixed at a value of 0.96. Additionally, I assume a unitary preference of the household. Putting everything together, the flow utility at time t can be written as follows:

$$
\begin{aligned}
u(\Omega_{it}, \mathbf{h_{it}}, \mathbf{o_{it+1}}) = \gamma_c log(c_{it}) + \sum_{j=m,w} \gamma_j(n_{it}) log(l_{ijt}) \qquad &\textit{(Consumption and Leisure)} \\
+ \sum_{j=m,w} \alpha_j(n_{it}) \mathbb{I}(o_{ijt} = o_h) \mathbb{I}(h_{ijt} > 0) \qquad &\textit{(Non-pecuniary benefit)} \\
- \sum_{j=m,w} S_j \mathbb{I}(o_{ijt+1} \neq o_{ijt}) \qquad &\textit{(Occupation Switching Cost)} \\
+ \varepsilon_{it}(\mathbf{o_{it+1}}, \mathbf{h_{it}}) \qquad &\textit{(Choice-specific Preference Shocks)} \\
\text{where } \varepsilon_{it} \sim Gumbel(0,1) &
\end{aligned}
\tag{8}
$$

5 Estimation: Simulated Methods of Moments

Table 5 summarizes parameters in the model with brief descriptions.

Description	Notation	Number of Params
Coefficients on log(consump), log(leisure)	γ_c, γ_j	3
Occupation switching cost	S_j	2
Non-pecuniary benefit of high flexibility	$\alpha_j(n)$	4
Coefficients on log(leisure) when a young child exists	$\tilde{\gamma}_j$	2
Human capital accumulation	ρ_j	2
Occupation-specific full-time wages	$\vec{\beta}_j(o)$	16
Occupation-specific part-time wage penalties	$g_j(o,h)$	8
Covariance of wage shocks	Σ	2
Total Number of Parameters		39

Table 5: Summary of Parameters

5.1 Identification

As known, there is no one-to-one mapping from moments to parameters. However, in this section, I provide a broad description how each group of parameters are related to a set of moments selected in the estimation. In Table 6, I present a full set of moments used in the model by their broad categories, and which parameters of the model, broadly speaking, affect which set of the set of the moments.

Categories	Moments	Related Parameters
Consumption, labor supply	• Proportions of working hour options by gender • Proportions of working hour options by gender, year since first birth • Proportions of working hour options by gender, spouse's working options • Transition rates between working hour options by gender • Transition rates between working hour options by gender, in the year of the first childbirth	$\gamma_c, \gamma_j, \bar{\gamma}_j$
Occupational Choice	• Proportions of occupations by gender • Proportions of occupations by gender, working options • Proportions of occupations by gender, year since first birth • Proportions of occupations by gender, spouse's occupations • Transition rates between occupations by gender • Transition rates between occupations by gender, in the year of the first childbirth	$\alpha_j(n), S_j$
Human capital process	• Correlation between current hours and future wages conditional on current observable characteristics • Average level of experience at final period by gender	ρ_j
Occupation-specific full-time wages	• OLS regression of log wages on education and occupation, by gender, full-time only • OLS regreession of log wages on experience and occupation, by gender, full-time only	$\beta_0(o), \beta_1(o)$ $\beta_2(o), \beta_3(o)$
Part-time wage discount rates	• Ratio between predicted part-time wages and predicted full-time wages conditional on education, occupation, and gender • Average accepted wages by occupation and working hour options	$g_j(o, h)$
Var-Cov of wage shocks	• Variance of residual wages after running OLS regression of log wages on education, experience, and occupation, by gender	Σ

Table 6: List of Parameters & Identifying Moments

To match the observed distributions of hours worked, I use direct proportions of working hour options by observable characteristics. These moments help to identify parameters related to the labor supply in the absence of children, $\gamma_c, \gamma_m, \gamma_w$. To capture the relative division of labor within the household, I also include proportions of working hour options by spouse's working status. Lastly, the changes in the labor supply around childbirth can identify the changes in the values of non-working hours when there is a young child in the household.

Parameters related to occupational choices are also identified with a similar set of moments. First, given the wage differentials, proportion of individuals with high flexibility occupation would help identifying the value of non-pecuniary benefit in the absence of children. Given the base levels of non-pecuniary benefits and hours worked in previous period, the different drop-out rates from the labor force across occupations will be correlated to the changes in the non-pecuniary benefits. Lastly, average transition rates across occupations are closely related to the switching cost parameters.

The parameters governing the human capital accumulation, ρ_m, ρ_w, are identified through the future wage differentials across individuals who choose to work different working hours conditional on all other observable characteristics. In particular, I use changes in wages conditional on previous working options conditional on education and experience.

Occupation-specific full-time wage equations, $\vec{\beta}_j(o)$, are identified using indirect inferences. Using the simulated data, I run OLS regressions of log wages on experience and occupation by gender conditional on working full-time positions, and match the moments with the OLS estimates from the true data.

The part-time wage discounts are also relying on the method of indirect inference. First, I fit wages on observable characteristics using real and simulated data sets, and get predicted wages from those models. Then I compute ratios between the predicted part-time wages and the predicted full-time wages, and use these ratios as moments to calibrating the part-time wage discount functions, $g_j(h, o)$.

Lastly, the variances of the residual wage shocks, Σ, uses the variance of the residual wages after running gender-specific OLS regressions with log wages on education, experience, and occupation.

5.2 Implementation

In this section, I describe the solution of the model, the simulation of moments, construction of the objective function, and the optimization method.

5.2.1 Solution

Since the model is in finite horizon, I solve the model from the terminal period. At the terminal period, T, all wives become age of 45, and the value of the next period, V_{T+1} is normalized to 0. As the next period occupations do not play a role in the next period, no one would switch from the given occupation, $\vec{o}_T$ unless they have extremely positive preference shocks from such choices.

$$V_T = \max_{\vec{h}_T, \vec{o}_{T+1}} u_T(\Omega_T, \vec{h}_T, \vec{o}_{T+1}) \tag{9}$$

Then, in period $t = T - 1$, the household problem can be written as follows:

$$V_{T-1} = \max_{\vec{h}_{T-1}, \vec{o}_T} u_{T-1}(\Omega_{T-1}, \vec{h}_{T-1}, \vec{o}_T) + \beta \mathbb{E}[V_T(\Omega_T) | \Omega_{T-1}, \vec{h}_{T-1}, \vec{o}_T] \tag{10}$$

The expectation in the value of the next period is taken over both choice-specific preference shocks and the wage shocks in the terminal period for both spouses. In the model, $n_{it}, \vec{E}_i, \vec{o}_{it}$ are discrete and have only a few possible values; where as $\vec{X}_{it}, \vec{\eta}_{it}$ have either continuous domain or many possible values. Here, the objective is to evaluate the $\mathbb{E}V_T := Emax_T$ at each point in the state space. To reduce the computational burden, I select a subset of the state space values to evaluate the value functions along these continuous or pseudo-continuous state variables. Specifically, I use the following procedures:

1. Compute the choice-specifc values V_T^d at the subset of the state space. In particular, I use the following grid points for experience levels: $\tilde{X}_{ijt} = \{5, 7, 10, 13, 15, 20, 25, 35, 50\}$. For wage shocks, I use the sparse grids illustrated by Heiss and Winschel (2008). I denote these sets of grid points as $\tilde{X}_{ijT}$ and $\tilde{\eta}_{ijT}$, respectively.

2. Compute $\mathbb{E}_{\varepsilon}[V_T|\vec{\eta}_{iT}]$ at each values in $\tilde{\eta}_{ijT}$. As I assume that the choice-specific preference shock follows the Gumbel distribution, there is a closed-form solution for this expectation.

3. Approximate $\mathbb{E}_{\eta}[\mathbb{E}_{\varepsilon}[V_T|\vec{\eta}_{iT}]]$ using the sparse grid method by Heiss and winschel (2008). Note that the nodes, $\tilde{\eta}$ and the weights are computed using the nested rule for integral with Gaussian weight.

4. Now we have $Emax_T$ evaluated at each point in the $\tilde{X}$ values. Approximate the $Emax$ along full grid points of the experience levels using the method developed in Keane and Wolphin (1994, 1997, 2001). I use a polynomial regression of the third order for this approximation. The R-squares are well above the 0.99 in all periods.[16]

5.2.2 Simulation and Optimization

Given a set of parameter values, θ, the model produces the vector of simulated moments, $m(\theta)$. I use the simulation size of 20,000 households, and all the initial values of the initial state space are drawn from the empirical distributions in NLSY79 at wife's age 19 for high school graduates and at wife's age 24 for college graduates. There are 39 parameters in the model, and 240 moments are selected. The vector of moments are summarized in Table 6.

I use the simulated method of moments to estimate the model parameters. In words, the estimates would minimize the sum of squared distances between the data moments and the simulated moments. To normalize the different scales of the moments, I divide the distances by the values of the data moments. To put formally, the parameters are estimated to minimize the following objective function:

$$\hat{\theta} = argmin_{\theta} \sum \left(\frac{\hat{m} - m(\theta)}{\hat{m}} \right)' \left(\frac{\hat{m} - m(\theta)}{\hat{m}} \right) \tag{11}$$

The standard errors of the parameter estimates are computed using the standard GMM formula. However, as pointed out by Lise and Robin (2017), the moments are not necessarily smooth functions of the parameters. Thus, estimating standard errors using the numerical differentiation of the moments around the estimated values would be imprecise due to the non-smoothness. In this paper, I follow the procedures described in Lise

[16]Using higher order polynomials does not improve the R-squares.

and Robin (2017) to address this issue. I evaluate each moments at the equally-spaced grid points of each parameter θ_k around the estimated values fixing all other parameters at the estimated values. Then I fit each moment on the polynomial of degree 5 of the grid points around the estimated value, and I take the derivative of this polynomial at the estimated value as my estimate of the partial derivative of that moment by the k-th parameter evaluated at the estimated value.

5.3 Results

Table 7 shows the estimated parameters with their standard errors.

5.4 Numerical Analyses: Quantifying the Effects of Flexibility

6 Counterfactual Analyses

7 Conclusion

Param	Descriptions	Spouse	Value (S.E.)	
γ_c	coefficient on log consumption		1.95 (0.08)	
γ_m	coefficient on log leisure	Husband	0.94 (0.13)	
γ_w	coefficient on log leisure	Wife	0.85 (0.11)	
$\bar{\gamma_m}$	change in γ_m with child	Husband	1.82 (0.12)	
$\bar{\gamma_w}$	change in γ_w with child	Wife	3.28 (0.12)	
S_m	occupation switching cost	Husband	2.10 (0.22)	
S_w	occupation switching cost	Wife	5.49 (0.38)	
ρ_m	human capital accum. rates	Husband	1.20 (0.12)	
ρ_w	human capital accum. rates	Wife	5.51 (0.77)	
			High Flex	Low Flex
β_{0m}	intercepts in FT wage	Husband	1.80 (0.11)	2.13 (0.07)
β_{1m}	college premiums in FT wage	Husband	0.19 (0.09)	0.21 (0.04)
β_{2m}	returns to expr in FT wage	Husband	0.15 (0.02)	0.18 (0.01)
β_{3m}	returns to expr squared	Husband	-0.0072 (0.0006)	-0.0067 (0.0004)
β_{0w}	intercepts in FT wage	Wife	1.42 (0.09)	1.60 (0.04)
β_{1w}	college premiums in FT wage	Wife	0.26 (0.08)	0.30 (0.03)
β_{2w}	returns to expr in FT wage	Wife	0.12 (0.02)	0.18 (0.01)
β_{3w}	returns to expr squared	Wife	-0.0051 (0.0011)	-0.0057 (0.0004)
σ_m	variance of wage shocks	Husband	0.0049 (0.0083)	
σ_w	variance of wage shocks	Wife	0.0043 (0.0094)	
			High Flex	Low Flex
$\delta_m(h_1)$	wage penalty for **PT low**	Husband	0.31 (0.02)	0.72 (0.02)
$\delta_m(h_2)$	wage penalty for **PT high**	Husband	0.01 (0.01)	0.30 (0.01)
$\delta_w(h_1)$	wage penalty for **PT low**	Wife	0.30 (0.07)	0.61 (0.07)
$\delta_w(h_2)$	wage penalty for **PT high**	Wife	0.13 (0.04)	0.43 (0.04)
			No Child	Child
$\alpha_m(n)$	non-pecuniary benefit	Husband	0.42 (0.04)	0.77 (0.08)
$\alpha_w(n)$	non-pecuniary benefit	Wife	0.12 (0.04)	0.22 (0.05)

Table 7: Parameter Estimates

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Appendices

A A Measure for Occupational Flexibility

Why women's average flexibility score is lower than men's? For individuals having no college degree, men's flexibility are far higher than women's. This is because even for those low educated women, occupations usually require more strict time schedules compared to men's occupations. (women work in services industries where men work in more flexible settings). But even individuals with college degree, young women have lower flexibility compared to young men. This is because occupations which exclusively held by men (e.g., construction workers, production workers, electronic engineers) are more flexible in the beginning of the career path compared to occupations which are exclusively held by women (e.g., secretaries, administrative assistants)

B Supplemental Data: American Time Use Survey

American Time Use Survey consists of a nationally representative sample of individuals and provides information on individual's time use within a day together with a contextual information. Relevant information includes how much hours worked during the day, what time of the day they work, and the location of work. Consistent with the main NLSY79 sample, I restrict the sample to individuals who are at least high school graduates, and age between 19 to 45 for high school graduates and 24 to 45 for college graduates. The sample period includes years from 2003 to 2010.