Childcare Availability During Nonstandard Hours and Household Choices

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Abstract

Around 28% of all workers and 46% of low-educated workers with young children experience nonstandard work schedules, including evenings, nights, or weekends. However, childcare options are limited during these schedules. The core trade-off faced by households with young children during nonstandard schedules is higher wages due to the schedule premium but limited access to high-quality low-price childcare. Focusing on households with young children aged four and younger, I estimate a model of household maternal labor supply, childcare arrangements, and child skill development, allowing for heterogeneous wages, availability of childcare, and price-quality distributions during different schedules. This paper first estimates the magnitude of the schedule premium to range from 3.8% to 22.3%, depending on education and gender. The estimated model indicates that variation in childcare quality between standard and nonstandard schedules is crucial for understanding household behaviors. Having high-quality provider care available during nonstandard hours would significantly enhance the well-being of lower socioeconomic status (SES) households. Suppose Head Start (a higher-quality care option) is available during nonstandard hours and accessible to all eligible lower SES households. In that case, mothers in this group are 4.9% more likely to participate in the labor force, 20.5% more likely to enroll their children in formal provider care, and their children's skills improve by around 24.0%.

Keywords: nonstandard schedule, childcare arrangement, maternal labor supply

JEL codes: J13, J18, J21, J22, J31

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1 Introduction

Additional monetary compensations are generally paid or required for working nonstandard schedules (evenings, nights, or weekends). Among workers with young children, around 28% of them work some nontraditional hours. Households with young children are reported to have significant demand for childcare services during those schedules. However, during those hours, the availability of childcare options is limited. As the National Survey of Early Care and Education (NSECE) 2019 data reveals, only around 10% of center-based providers provide service during nontraditional hours.[1] To meet the demand for childcare during those nontraditional work schedules, the literature documents that households tend to rely more on informal care (relative or paternal care) and use multiple care arrangements. Even though relatives and home-based providers are more flexible with care hours, relative care is reported to have lower measured quality and is available to only approximately 54% of households. Home-based care, on the other hand, is generally more expensive. The core trade-off households face is higher wages during nonstandard hours due to the schedule premium but limited access to high-quality low-price childcare during those hours. The conflicts between work schedules and regulated childcare could potentially impede maternal labor market outcomes, formal care enrollments, and child skill development.

This issue is especially salient for households with lower socioeconomic status (SES), referring to those without a college education in this paper, as workers from lower SES households are more likely to self-select to work during nonstandard work schedules due to wage compensation. Based on the American Time Use Survey (ATUS) data, conditional on being employed and having children age below five, around 9% of workers with bachelor's degrees or higher experience nontraditional hours but around 46% of workers without college education experience nontraditional hours.[2]

Despite the limitations concerning childcare availability during nonstandard schedules, which may disproportionately affect lower SES households more, to the best of my knowledge, existing economic models ignore this aspect when analyzing child skill development and assessing policy impacts. I investigate this issue by estimating a model of maternal labor supply, childcare arrangement, and child skill development, considering heterogeneous wages, availability of childcare, and price-quality distributions during different schedules. The model's primary components revolve around nonstandard schedule choices, and this paper offers insights into understanding the childcare constraints that households with young

[1] See Table 24 in Appendix A. Similar patterns are also revealed in the Early Childhood Longitudinal Study, Birth Cohort (ECLS-B) data.

[2] This specific tabulation includes workers age between 18 and 50 who are not self-employed. Details are shown in Appendix A, Table 19 presents more details.

children face during nonstandard hours. This paper examines how frictions in accessing high-quality or affordable childcare services during nonstandard hours can impede maternal labor market outcomes, formal childcare usage, and child development for households from lower SES backgrounds.

More specifically, following the framework in and making extensions to Griffen [2019] and Chaparro et al. [2020], I incorporate multiple childcare options – providers who only operate during the standard schedule, providers who offer services during any schedule, relative care, paternal care, and maternal care – and allow each of the non-parental care options to have a heterogeneous price and quality distribution. They also vary with respect to the impacts on a child's development through quality, productivity, and time investment. The availability of relative care varies across households. Certain households lack access to care from relatives, while others may have relatives who assist solely during standard hours. Conversely, some can depend on relatives for care at any time. Providers offering only standard schedule services are inaccessible during nonstandard hours, and providers offering services during any schedule are available anytime. Regarding maternal labor supply choices, my model incorporates wage premiums for working during nonstandard schedules. A child's cognitive skill development is determined by the time inputs from both parents and care providers, as well as the quality of the different types of care the child receives.

This paper makes several findings. First, I rigorously estimate the magnitude of the schedule premium using the National Longitudinal Survey of Youth - 1997 Cohort (NLSY97) data. Switching entirely from working standard hours to working nonstandard hours increases the hourly wage by approximately 14.3% for workers without college education and 10.0% for workers with bachelor's or above degrees, respectively. Heterogeneity analysis reveals that the schedule wage premiums are comparatively higher for female workers than for male workers, ranging from around 15.9% to 22.3% for female workers and around 3.8% to 7.3% for male workers, with lower educated workers receiving relatively higher premiums.[3] Second, this paper finds that, for lower SES households whose mothers do not have college education, the schedule premium serves as a key reason to explain their choice of nonstandard work hours and their need for childcare services during these times. Once there is no wage premium, the fraction of nonstandard working hours among total working hours for mothers in this group decreases by 75.2%, and the fraction of nonstandard provider care hours among total provider care hours for households in this group decreases by 31.6%. Third, estimates from this paper show that the quality of providers offering care in any schedule is around one

[3]This observation should not be interpreted as evidence of wage discrimination. Instead, it can potentially be elucidated by the comparative advantages of female and male workers, or of lower- and higher-educated workers in various occupations, leading to heterogeneous distributions in jobs.

standard deviation lower than that of providers offering only standard schedule care. This is to say that frictions exist in the childcare market, and on average, households have no access to high-quality providers during nonstandard schedules. When the quality of providers who operate any schedule is improved by around one standard deviation to match the quality of providers who only operate standard schedules, lower SES mothers' labor participation increases by around 20.4% and provider care usage increases by around 61.2%.

To investigate what practical alternatives of existing policies can further improve the well-being of lower SES households, this paper conducts several counterfactual policy analyses regarding the Head Start program, which aims to provide higher-quality free care to low-income households, and regarding various types of subsidies, which assist low-income households through decreasing childcare costs. Among these various counterfactual analyses, enhancing the quality of childcare during nonstandard hours is demonstrated to exert the most significant impact. Having the higher-quality Head Start program available among providers who operate during any schedule and making it accessible to all eligible lower SES households results in a 4.9% increase in maternal labor participation, a 20.5% rise in provider care enrollment, and a 24.0% improvement in child skill for lower SES households. Suppose only lower SES households experience such a policy change; the maternal labor participation gap, formal care enrollment gap, and skill development gap between higher and lower SES households would be reduced by around 10.9%, 22.3%, and 13.0%, separately. Other price subsidies have limited ability to improve households' well-being without alleviating the friction of childcare quality among nonstandard hours. Even though price subsidies make childcare more affordable, they still do not solve households' demand for high-quality childcare during nonstandard schedules, which continues to deter households from using the service.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the model setting and household problem. Section 4 presents the data used for analysis and summary statistics for the primary data sets used. Section 5 illustrates how the model is estimated. Section 6 presents the estimates and goodness of the model fit by comparing the model moments with the data moments. Section 7 simulates and analyses several counterfactual scenarios. Section 8 concludes the paper.

2 Literature Review

Schedule compensation is prevalent in practice. Based on the survey reports from Culpepper and Inc. [2008] and Culpepper and Inc. [2010], more than 90% of companies pay shift differentials to hourly employees, and around 36% of companies pay shift differentials to salaried employees. Kostiuk [1990] estimates the average shift premium to be around 8.2% for male manufacturing workers. Schumacher and Hirsch [1997] documents that for registered nurses the evening shift differential is approximately 4%, and the night shift differential is around 11.6%. Lanfranchi et al. [2002] estimates a 16% shift premium for full-time blue-collar workers using French data. To assess workers' willingness to pay for diverse work arrangements, Mas and Pallais [2017] conducts a nationwide discrete choice experiment throughout the job application process. Regarding schedule differentials, they estimate that employees require a premium of 14% for evening shifts and a premium of 19% for weekend shifts. I seriously estimates the magnitude of the schedule premiums using the NLSY97 data. When workers transition from working entirely in standard hours to working entirely in nonstandard hours, in this paper the wage premiums are estimated to range from 3.8% to 22.3%, depending on education and gender.

These additional wage differentials are expected to have more distinct impacts on lower SES workers' work choices. Hamermesh [1999] states that evening and night schedules are inferior, and higher-income workers are more likely to transit away from these schedules. Kostiuk [1990] and Lanfranchi et al. [2002] point out that self-selection is essential in understanding workers' schedule choices, and workers with lower day-shift incomes self-select to work more nontraditional hours. Consistent with these statements, Presser and Ward [2011] and Enchautegui [2016] report that lower SES workers are less likely to participate in the labor force and, if employed, are more likely to work nonstandard schedules.

The demand for childcare services during nonstandard schedules is significant, but childcare options are limited during these hours. Schilder et al. [2023] documents that around 40 percent of young children aged below five use childcare during some nontraditional hours. Collins et al. [2000] and Henly et al. [2006] report that there exists a shortage of childcare services that adequately accommodate unconventional and atypical work schedules, which is particularly true in lower-income neighborhoods. Households with nontraditional work schedules are reported to be significantly less likely to use formal care such as center-based care (Kimmel and Powell [2006]) and more likely to rely on informal care (relative or paternal care) and use multiple care arrangements (Folk and Yi [1994], Hepburn [2018], Schilder et al. [2023]). However, Flood et al. [2022] documents that relative care is, on average, of lower quality.

It is documented in Ben-Ishai et al. [2014], Enchautegui et al. [2015], and Pilarz et al. [2019] that conflicts between work schedules and regulated childcare can potentially hinder maternal labor market outcomes and formal care enrollments, particularly for lower-SES households. Despite the constraints on childcare availability during nonstandard schedules, particularly impacting lower SES households, to the best of my knowledge, existing economic models generally overlook this factor in their analyses of child skill development and policy impact assessments.

My paper contributes to the literature in the following aspects. Although the literature has broadly discussed how maternal employment can influence the child's skill development (Waldfogel et al. [2002], Ruhm [2004], James-Burdumy [2005], Bernal [2008], Bernal and Keane [2010], Agostinelli and Sorrenti [2021], Nicoletti et al. [2023]), the channels discussed mostly focus on the trade-offs between time investment and monetary investment, and none of them pay specific attention to the schedule channel. However, parental work schedule is documented to be highly associated with childcare usage (Han [2004], Ben-Ishai et al. [2014], Enchautegui et al. [2015], Pilarz et al. [2019]). My paper bridges the two streams of literature by adding the schedule arrangement channel. In my model, childcare arrangements while the mother is working can have various impacts on the child's outcomes. The potential care providers to whom the mother has access across different schedules, and their quality, can adversely impact the mother's working behavior.

There is another branch of literature that uses structural model to measure potential policy impacts on maternal labor supply, childcare usage, and child development (Griffen [2019], Borowsky et al. [2022], Berlinski et al. [2024]), or to understand the technology of skill formation for children (Todd and Wolpin [2003], Cunha et al. [2010], Del Boca et al. [2014]). Certain simplifications are usually made over the aspects that are important for understanding the schedule constraints by grouping all the non-parental care together (e.g.Griffen [2019]) or by assuming homogeneous quality within each type (e.g.though Berlinski et al. [2024] allows two levels of center qualities, it assumes homogenous quality within paid caregivers, and within relatives). None of these papers have seriously considered the potential availability constraints among nonstandard schedules, although Adams and Katz [2015] points out that care subsidies could potentially enhance the well-being of low-income families by addressing parents' childcare needs during nonstandard hours. These aspects are the primary focus of this paper.

3 Model

I develop a static model focused on households with young children under the age of five, where mothers are present. The household's decisions revolve around maternal labor supply and childcare arrangements (including maternal care, paternal care, provider care, and relative care) during standard and nonstandard hours. In this context, standard hours are defined as 8 a.m. to 6 p.m., Monday through Friday, and nonstandard hours include all time outside this range, inspired by the settings in Presser [2003], Enchautegui et al. [2015], Enchautegui [2016], and Pilarz et al. [2019].[4]

The supply of paternal labor, regarding both hours and schedule, is assumed to be exogenous.[5] Even though paternal labor supply is important, it is almost unaffected by the presence of young children and is not the focus of this paper. Kleven et al. [2019] shows that the birth of a child has a significant impact on the mother's labor decisions but has almost no effect on the father's labor participation or work hours, both in the short-term and long-term, using Danish data. Using the same methodology, in Appendix B, I show similar patterns using the US data and additionally regarding schedule choices, that the birth of a child decreases the mother's non-day-shift schedule by around 10% but does not have significant impacts on father's work schedule. Within the household, when there are time conflicts between work and care, the mother is likely to be the person to adjust her schedule.

Schedule enters the model through multiple channels. All else being equal, the hourly wage is determined by the schedule chosen by the worker and the worker's characteristics. And the available sources of childcare vary depending on the schedule. The details of the model are explained in the following sections.

3.1 Model Setting

Choice Set

Each household makes decisions regarding two main aspects: maternal labor supply and childcare arrangements, both of which depend on schedules. For writing convenience, starting from this section and from now on, '*std*' represents standard, '*nstd*' represents nonstandard, τ represents hours, '*ns*' represent fraction of hours in nonstandard hours, and subscripts m, f, r, p separately denote four care options, the mother, the father, relative, and provider.

Specifically, the unitary household decides how much maternal labor to supply L_m and what proportion to work in nonstandard hours ns_m^{work}. There are four primary sources of childcare: maternal care, paternal care, relative care, and provider care. Paternal care is contained in the choice set only for married households, and the household decides how many paternal care hours to use τ_f and what fraction to use in nonstandard hours ns_f^{care}. Relative care is accessible only to some households, contingent upon availability with probability Pr_r.

[4] There are multiple ways of defining nonstandard schedules. Presser [2003] defined nonstandard work shifts as working more than half of the total hours outside of 8 a.m. to 4 p.m.; Enchautegui et al. [2015] defined it similarly but also included weekends as nonstandard schedule; Enchautegui [2016] defined nonstandard schedule as working most of the hours outside of 6 a.m. to 6 p.m. or on weekends. This paper's definition of standard hours takes the union of the definitions in the literature.

[5] The main reason for this assumption is for computational tractability.

Conditional on being available, only a subset of relatives is willing to provide care during nonstandard hours, the probability of which is assumed to be Pr_r^{nstd}. For a household whose relative is willing to provide care in all schedules, the household makes decisions on how much relative care to use during standard hours and nonstandard hours, $\tau_r^{std}, \tau_r^{nstd}$. For a household whose relative is only willing to provide care in a standard schedule, the household only decides how many standard hours of relative care to use τ_r^{std}. In the childcare market, there are two types of providers: providers that only operate during standard hours ps and providers that operate during any schedule, both standard and nonstandard hours, pa. If the household demands childcare services during standard hours, both types of providers are in the household's choice set; however, for nonstandard hours, only the second type is available. The household decides which provider to use for standard hours $P^{std} \in \{ps, pa\}$; and how many hours of provider care to use in standard and nonstandard hours, $\tau_p^{std}, \tau_p^{nstd}$. The maternal care among standard and nonstandard hours, $\tau_m^{std}, \tau_m^{nstd}$, are automatically determined through the process. For low-income households who are eligible for childcare subsidies, the household makes one more choice on whether to take the subsidy or not I^S.

Time Constraints

Since the setting for the time is one of the key aspects of this paper, I start by introducing the time constraints of the model.

$$\text{care needed:} \quad T_c^{std} = \tau_m^{std} + \tau_f^{std} + \tau_r^{std} + \tau_p^{std} \tag{1}$$

$$T_c^{nstd} = \tau_m^{nstd} + \tau_f^{nstd} + \tau_r^{nstd} + \tau_p^{nstd} \tag{2}$$

The total amount of care needed by the child is T_c and is divided into hours of care needed in standard hours T_c^{std} and in nonstandard hours T_c^{nstd}.[6] Under each schedule, standard and nonstandard, the needs for the care are fulfilled by maternal care τ_m, paternal care τ_f, relative care τ_r, and provider care τ_p as are shown in equation (1) and (2).

$$\text{mother:} \quad T^{std} = \tau_m^{std} + l_m^{std} + L_m^{std}, \tag{3}$$

$$T^{nstd} = \tau_m^{nstd} + l_m^{nstd} + L_m^{nstd}, \tag{4}$$

$$\text{father:} \quad T^{std} = \tau_f^{std} + l_f^{std} + \overline{L_f^{std}}, \tag{5}$$

$$T^{nstd} = \tau_f^{nstd} + l_f^{nstd} + \overline{L_f^{nstd}}, \tag{6}$$

The mother is endowed with (T^{std}, T^{nstd}) hours and she distributes those hours among maternal care τ_m^{std} τ_m^{nstd}, leisure l_m^{std} l_m^{nstd}, and work L_m^{std} L_m^{nstd} in standard and nonstandard hours.

[6] T_c is calculated as the total hours of the week minus the total sleeping time of the child.

The mother can choose not to work, work part-time, or work full-time, $L_m \in \{0, 20, 40\}$. She also decides what proportion of her total work hours is during nonstandard hours, $ns_m^{work} \equiv \frac{L_m^{nstd}}{L_m}$; $ns_m^{work} \in \{0.0, 0.11, 0.52, 0.90\}$ for half-time workers and $ns_m^{work} \in \{0.0, 0.09, 0.23, 0.49\}$ for full-time workers.[7] The father's time constraints are comparable with the mother's, but his labor decisions are assumed to be exogenous. The father's total labor hours $\overline{L_f}$ and labor schedule $\overline{ns_f^{work}} \equiv \frac{\overline{L_f^{nstd}}}{\overline{L_f}}$ are drawn from the population distribution based on his educational attainment.[8] Excluding working hours, the father, if present, distributes the rest of his hours among paternal care τ_f^{std} τ_f^{nstd}, and leisure l_f^{std} l_f^{nstd}. τ_f and $ns_f^{care} \equiv \frac{\tau_f^{nstd}}{\tau_f}$ are paternal care choices, and the father provides total amount of τ_f hours of care, $\tau_f \in \{0, 3.75, 9, 21\}$, and provides ns_f^{care} fraction of the total paternal hours during nonstandard hours, $ns_f^{care} \in \{0, 0.5, 1\}$.[9]

$$L_m^{std} \leq \tau_f^{std} + \tau_r^{std} + \tau_p^{std}, \tag{7}$$

$$L_m^{nstd} \leq \tau_f^{nstd} + \tau_r^{nstd} + \tau_p^{nstd}, \tag{8}$$

In equation (7) and (8), I assume that when the mother chooses to work L_m^{std} hours during the standard schedule or work L_m^{nstd} hours during the nonstandard schedule, she needs someone to take care of the child for at least the same amount of hours. The care can be provided by the father τ_f^{std} τ_f^{nstd} which are zeros if it is a single-mom household, by relatives τ_r^{std} τ_r^{nstd} which are zeros if relatives are unavailable or unwilling to care for the household, or by providers τ_p^{std} τ_p^{nstd}. The gap between L_m^{std} and $\tau_f^{std} + \tau_r^{std} + \tau_p^{std}$ is the additional leisure in standard hours the mother enjoys by using childcare services, and the same applies to

[7] $\{0.0, 0.11, 0.52, 0.90\}$ are the 25%, 50%, 75% and 90% quantile of the schedule distribution for half-time workers; and $\{0.0, 0.09, 0.23, 0.49\}$ are the 25%, 50%, 75% and 90% quantile of the schedule distribution for full-time workers. Referring to how much power workers have over their work schedule. Using the *National Study of Employers* data, the Council of Economic Advisers CEA [2010] presents that, in 2007, 79% of employers permitted at least some of their workers to periodically modify their starting and ending times within a certain range of hours; 37% of employers allow most or all employees to periodically modify their starting and ending times within certain range of hours. This report also shows that using *Current Population Survey* data in 2004, only 28% of full-time workers and around 39% of part-time workers report this type of schedule flexibility. The gap in answers between employers and employees could possibly be due to the unawareness of such options.

[8] The paternal labor schedule distribution is based on the precise calendar information provided in the NSECE 2019 data. The total weekly labor supply distribution is estimated based on the average weekly work hours during the first four years after the first child's birth, using the NLSY97 panel data. This is to address concerns that the non-working behavior is exaggerated when using cross-sectional data to estimate the population work distribution of fathers with young children.

[9] {3.75,9,21} are the 25%, 50%, 75% quantile of the paternal care distribution, conditional on paternal care being positive.

additional leisure in nonstandard hours. The gap between T_c^{std} and $\tau_f^{std} + \tau_r^{std} + \tau_p^{std}$ is the amount of maternal care in standard hours, and the same applies to maternal care in nonstandard hours.[10]

Budget Constraint

$$C_{hh} + C_c(\tau_r, \tau_p^{std}, \tau_p^{nstd}, P^{std}, I^S) = I_{mother}(L_m, ns_m^{work}) + I_{father}(\overline{L_f}, \overline{ns_f^{work}}) + Y, \tag{9}$$

Outflows of the budget include household consumption C_{hh}, and childcare expenditure C_c which is determined by childcare arrangements on hours of care $\tau_r, \tau_p^{std}, \tau_p^{nstd}$, which provider is used in standard hours P^{std}, and whether using the subsidy I^S if it is accessible.

Inflows of the budget come from the mother's labor income I_{mother}, the father's labor income I_{father}, and the household non-labor income Y. The mother's and the father's labor incomes are separately calculated as the products of labor hours and hourly wages. The mother's labor income depends on her labor hours L_m and the labor schedule she chooses ns_m^{work}. The father's labor income is exogenously determined by his labor hours $\overline{L_f}$ and labor schedule $\overline{ns_f^{work}}$. Non-labor family income is also exogenous and drawn from the population distribution based on educational attainment.

The wage function is displayed in equation (10). Other than depending on those commonly considered worker characteristics, the hourly wage in this paper further depends on the worker's work schedule choices ns^{work}. Distribution of the wage shock ϵ_w is heterogeneous and depends on the controls $X \equiv \{age, full-time, education, race\}$. Details about the wage function and its identification are discussed in Section 5.1.

$$\log w = \alpha_w^{edu} ns^{work} + \beta_{w0} + \beta_{w1} age + \beta_{w2} age^2 + \beta_w^{full-time} + \beta_w^{edu} + \beta_w^{race} + \epsilon_w(X), \tag{10}$$

Child Skill Production Function

I assume the quality of care $\{q_{parent}, q_r, q_{ps}, q_{pa}\}$ follows a normal distribution, the mean of which depends on the household's characteristics, race and mother's educational attainment. $q_{parent}, q_r, q_{ps}, q_{pa}$ denote the quality of parental care, the quality of relative care, the quality of providers who operate only during standard hours, and the quality of providers who operate on any schedule, separately. As is pointed out by Bassok and Galdo [2016], there

[10] Care provided is capped by care needed by the child. There might be concerns that based on the settings in equation (7) and (8), maternal labor supply during nonstandard hours is capped by T_c^{nstd} which are calculated as the total nonstandard hours minus the child's sleeping hours. In the NSECE 2019 data, only less than 2% of the mothers with children aged below five worked more than T_c^{nstd} hours during a nonstandard schedule, no matter how T_c^{nstd} is defined.

are disparities among different communities in the availability of high-quality preschool programs. Education-related and race-related quality parameters $\gamma_j^{edu}\gamma_j^{race}$ reflect the potential segregation possibilities. γ^{hs} allows the quality distribution to differ depending on whether the household has access to the Head Start program, which is explained in detail later.

$$q_j = \gamma_{j0} + \gamma_j^{edu} + \gamma_j^{race} + E^{hs}\gamma_{j=ps}^{hs} + \epsilon_j^q$$
$$\text{where } j \in \{parent, r, ps, pa\} \text{ and } \boldsymbol{\epsilon^q} \sim N(0, \boldsymbol{\Sigma}_{4\times4}) \tag{11}$$

For a given quality set, the child's skill at the end of the period h_1 is produced based on the following production function.

$$\ln h_1 = \delta_0 + \delta_1 \ln h_0 + \sum_{i\in\{std,nstd\}} \left\{\delta_{parent}(h_0)\frac{\tau_m^i + \tau_f^i}{T_c} q_{parent} + \delta_r(h_0)\frac{\tau_r^i}{T_c} q_r + \delta_p(h_0)\frac{\tau_p^i}{T_c} q_p^i\right\} + \epsilon_h, \tag{12}$$

$$\text{where } q_p^{std} \in \{q_{ps}, q_{pa}\},\ q_p^{nstd} = q_{pa}.$$

The skill production function follows Chaparro et al. [2020] and Griffen [2019]. h_0 is the initial inherited skill. The productivity of time investment, $\delta_j(h_0)$ where $j \in \{parent, r, p\}$, depends on initial skill h_0. When δ_j is positively correlated with h_0, the productivity of time investment is higher for children with higher initial skills. When δ_j is negatively correlated with h_0, the productivity of time investment is lower for children with higher initial skills.

Provider quality in standard hours, q_p^{std}, is determined by household choices. There are two types of providers inside the model: one group of providers only opens during standard hours, and the quality drawn is q_{ps}; the other group of providers provides service during any schedule, and the quality drawn is q_{pa}. For any hours used during nonstandard hours, care quality q_p^{nstd} equals q_{pa} based on the schedule setting. For any hours used during standard hours, the household chooses to use the provider which provides higher utility. It is to say q_p^{std} equals to the quality, either q_{ps} or q_{pa}, that can generate higher utility. This setting implicitly allows for switching, and the provider used in standard hours is allowed to be different from the provider used in nonstandard hours. Conditional on quality, care hours, and child's initial skill being the same, providers have the same productivity, $\delta_p(h_0)$.

Childcare Price Function

Relative care is free with a certain probability. If the household does not receive free care, the price depends on the quality and the type of the care. The price for parental care is assumed to be zero.

$$
\begin{gathered}
\ln p_k = \beta_{k0} + \beta_{k1} q_k + \epsilon_k^p \\
\text{where } k \in \{r, ps, pa\} \text{ and } \boldsymbol{\epsilon^p} \sim N(0, \boldsymbol{\Sigma}_{3\times 3})
\end{gathered} \tag{13}
$$

p_k is the price for different types of care. q_k is the care quality, and ϵ_k^p is the price shock. Since price shock is allowed, at the ex-post stage, price and quality are not one-to-one mapped to each other. For example, at the ex-post stage, different households can receive different prices for the same quality from the same type of provider. This is unrelated to price discrimination. Conditional on quality being the same, it is assumed that the provider offers one price for all children of the same age. However, heterogeneous prices over quality could be caused by the following reasons. Prices may differ among providers of the same type and quality based on location, due to varying demand in different markets. Furthermore, different families may have varying capacities to search for childcare services.

Household Preferences

$$
U = \ln C_{hh} + \gamma_{l_m} \ln l_m + \gamma_{l_f} \ln l_f + \gamma_{h_1} \ln h_1 + \gamma_{parent} \ln \sum_{i \in \{std, nstd\}} (\tau_m^i + \tau_f^i) \tag{14}
$$

The household cares about the household consumption C_{hh}, the mother's and the father's leisure l_m l_f, and the child's development at the end of the period h_1. γ_{parent} allows the family to benefit from (if > 0) or to have distaste from (if < 0) using parental care directly through preference other than through the child's skill, consumption, or leisure.

3.2 Potential Benefit Sources

Conditional on household income, each household faces various potential benefit sources. Head Start and Early Head Start, as well as childcare price subsidies funded by the Child Care and Development Fund (CCDF) are the two benefits considered in this paper. These are the two primary childcare policies that aim to help low-income households with young children to improve cognitive achievement or maternal labor participation. Schedule-related counterfactual policy rules can possibly be integrated into the existing policies. Settings for Head Start and subsidies refer to the settings in Griffen [2019].

Head Start[11]

The Head Start (HS) programs primarily serve young children from low-income households. From the 2019 report by the US Department of Health and Human Services - Administration for Children and Families, more than 95% of the Head Start preschool services and around 60% of the Early Head Start services are provided in center-based settings.[12] There are variations in hours of service per day and days of care per week, and each Head Start program is required to provide at least 1,020 annual hours, which is approximately 20 hours per week.[13] Referring to Griffen [2019], Head Start accessibility is as follows.[14] Households with incomes below 130% of the federal poverty line are potentially eligible for the Head Start program and have access to the program with a certain probability. Notably, γ_1^{hs} is assumed to be positive, meaning households with incomes below the 100% federal poverty threshold have a significantly higher likelihood of gaining access to this program.[15]

$$\pi_{hs} = \begin{cases} \dfrac{1}{1+exp(-\gamma_0^{hs} - \gamma_1^{hs} I\{hhinc > \bar{y}^{hs}\})}, & \text{if } hhinc < 130\% \bar{y}^{hs}, \text{ eligible} \\ 0 & \text{, otherwise} \end{cases}$$

[11]Based on the definition from the US Department of Health and Human Services, throughout the discussions, "unless otherwise specified, the term Head Start refers to the Head Start program as a whole, including Head Start services to preschool children; Early Head Start services to infants, toddlers, and pregnant people; services to families by American Indian and Alaska Native (AIAN) programs; and services to families by Migrant and Seasonal Head Start (MSHS) programs." From 2004 to 2019, the HS appropriations had increased from around 6.6 billion to around 10 billion.

[12]Head Start Program Facts: Fiscal Year 2019.

[13]Based on Head Start Services Snapshot 2020-2021 by Office of Head Start, 88.6% of all funded enrollment slots are provided in center-based option. 81.2% of center-based funded enrollment slots are with greater or equal to 1,020 annual hours for HS preschool children or 1,380 annual hours for EHS children; and 18.8% are with lower hours.

[14]HS preschool services are primarily for children aged three to four, and EHS services are mainly designed for younger children. Based on the 2019 report, most granted programs provide both HS preschool services and EHS services. Among the grantees, 29% provide HS preschool services only, 30% provide EHS services only, and around 58% provide both services. In the model, I assume the accessibility probabilities to HS are the same for younger and elder children. It is to say that the model assumes that the accessibility probability to EHS for children ages below three is the same as the accessibility probability to HS preschool for children ages between three and four. Related parameters are identified through the eligibility of HS preschool services for children under five.

[15]Based on the policy rules, to be eligible, households' incomes must be below the 100% federal poverty level. Programs may accept households whose incomes are beneath 130% if there are unfilled spots.

where $\bar{y}^{hs}$ is the 100% federal poverty level in 2019, and I divide them by fifty-two to be consistent with the weekly setting.

$$\bar{y}^{hs} = \frac{1}{52} \times \begin{cases} \$19,720, & \text{if family size} = 2 \\ \$24,860, & \text{if family size} = 3 \\ \$30,000, & \text{if family size} = 4 \\ \$35,140, & \text{if family size} = 5 \\ \$40,280, & \text{if family size} = 6 \\ \$45,420, & \text{if family size} = 7 \\ \$50,560, & \text{if family size} = 8 \end{cases}$$

Since HS and EHS are mostly provided under center-based settings and based on the fact that only around 10% of center-based providers operate during nontraditional hours, in the model, I assume that the Head Start program can only be provided by providers who operate only during standard hours, ps, and can provide $\bar{h}^{hs} = 20$ hours of higher quality free care per week. The accessibility is drawn from the following Bernoulli distribution.

$$E^{hs} \sim \mathbb{B}(1, \pi_{hs})$$

Subsidy

Referring to Griffen [2019], the key features of the subsidy program funded by the Child Care and Development Fund (CCDF) are threefold. First, there is an income eligibility cutoff, $\bar{y}^s$, and households are eligible for subsidies if they participate in the labor market and their incomes fall below this threshold. Second, households using the childcare subsidy must pay an out-of-pocket copay, $\psi(hhinc)$, which is a fraction of household income. Third, a rate ceiling, rc, is imposed: for any subsidized childcare priced below the rate ceiling, the marginal cost is zero; and for childcare priced above the rate ceiling, the household must pay the difference between the actual price and the rate ceiling.[16]

Due to factors such as waiting lists and market frictions, not all eligible households can access the subsidy program. For those who are eligible, accessibility of subsidy is drawn from

[16] Under the Child Care and Development Block Grant (CCDBG), the primary federal program that aims to assist childcare, there are state-level variations within the framework of federal guidelines Schulman [2019]. However, the data is not granular enough to support the estimation of state-level variations, and this paper's childcare subsidy parameters represent the nationwide population-weighted averages across states.

the following Bernoulli distribution.

$$\pi_s = \begin{cases} \dfrac{1}{1+exp(-\gamma_0^s)} & \text{if } I\{L>0\}I\{hhinc<\bar{y}^s\}=1 \\ 0 & \text{otherwise} \end{cases}$$

$$E^s \sim \mathbb{B}(1,\pi_s)$$

The provider care cost under subsidy is as follows.[17]

$$C_c^{p,\text{under}S} = \psi \times hhinc + \sum_{i\in\{std,nstd\}} (p^i - rc)\tau_p^i I\{p^i > rc\} \tag{15}$$

Based on the size of the copay, the household makes decisions on whether to use the subsidy. Households will only take the subsidy if the loss from the fundamental copayment does not offset the benefits from the decreased marginal rate. In other words, the household will choose not to take the subsidy, $I^S = 0$, if the original cost without subsidy is low enough and is below $C_c^{p,\text{under}S}$; and the household will choose to take the subsidy, $I^S = 1$, if vice versa. Incorporating both Head Start and subsidies into consideration, the actual provider care cost paid by the household is C_c^p.

$$\begin{aligned} C_c^p =& (1-E^s(I^S=1))\Big[\big(1-E^{hs}(P^{std}=ps)\big)\min\{\tau_p^{std},\bar{h}^{hs}\}p_p^{std} + \max\{0,\tau_p^{std}-\bar{h}^{hs}\}p_p^{std} + \tau_p^{nstd}p_p^{nstd}\Big] \\ &+ E^s(I^S=1)\Big[\psi \times hhinc + \big(1-E^{hs}(P^{std}=ps)\big)\min\{\tau_p^{std},\bar{h}^{hs}\}(p_p^{std}-rc)I\{p_p^{std}>rc\} \\ &\quad + \max\{0,\tau_p^{std}-\bar{h}^{hs}\}(p_p^{std}-rc)I\{p_p^{std}>rc\} + \tau_p^{nstd}(p_p^{nstd}-rc)I\{p_p^{nstd}>rc\}\Big] \end{aligned} \tag{16}$$

P^{std} is the household's choice of which provider to use in the standard schedule. If using a provider who only operates in standard hours $P^{std} = ps$ and the provider price in standard hours is $p_p^{std} = p_{ps}$. If using a provider who operates during any schedule $P^{std} = pa$ and the provider price in standard hours is $p_p^{std} = p_{pa}$. The provider price in nonstandard hours equals the price of the any-schedule provider $p_p^{nstd} = p_{pa}$.

3.3 Timing

At the beginning of the period, the household is endowed with information about the initial skill of the child h_0, the skill production shock ϵ_h, the wage shock ϵ_w, and the non-labor family income Y.

Since benefits accessibility depends on household income, maternal labor decisions can explicitly affect eligibility and accessibility of those benefit sources. I simplify the timeline

[17] Household income here refers to household income before any subsidy.

by assuming the household draws the set of benefits accessibility conditional on potential household income before making decisions. This is to say, the household knows ahead of time whether they will obtain those benefits under different household income levels.

For the married household, the father's work hours $\overline{L_f}$ and work schedule $\overline{ns_f^{work}}$ are drawn from the population distribution depending on his education and known to the household. As for parental care, the household takes a draw of parental quality shock ϵ^q_{parent}, and the paper assumes that paternal and maternal care quality within the household is the same.

Regarding relative care, the household takes a draw at the beginning of the period and learns if there are relatives nearby and willing to take care of the child, $I_r^{available}(\boldsymbol{Z})$, whose probability follows a logit function and depends on household's characteristics $\boldsymbol{Z}$ presented in equation (17). Conditional on relatives are willing to provide care, the household also learns if it is free of charge, I_r^{free}, whose probability based on equation (18); and learns if relative care is available in nonstandard schedule I_r^{nstd}, which is drawn from the Bernoulli distribution with probability Pr_r^{nstd}. Quality shock ϵ_r^q and price shock ϵ_r^p, if not free, are learned at the same time.

Referring to provider care, this paper assumes there are two types of providers: those who operate only during the standard schedule and those who operate during any schedule. The household takes separate draws from both pools of providers. The household draws a quality-price-shock bundle, $\{\epsilon^q_{ps}, \epsilon^p_{ps}\}$, from the pool of providers who only operate during the standard schedule; and draws another quality-price-shock bundle from the pool of providers who provide service in any schedule, $\{\epsilon^q_{pa}, \epsilon^p_{pa}\}$.

Probability of Relative Available and Willing to Provide Care

Equation (17) is the probability function (logit model) of availability of relative care, where $\tilde{\boldsymbol{Z}}$ is a vector of household's characteristics, including education, race, and marital status.

$$Pr_r(\boldsymbol{I}_r^{available} = 1|\tilde{\boldsymbol{Z}}) = \frac{1}{1 + e^{-(\delta_{r0} + \tilde{\boldsymbol{Z}}'\boldsymbol{\delta}_r)}} \tag{17}$$

Probability of Free Relative Care

Approximately 20% of care provided by relative incurs a cost in the NSECE 2019 data, with other datasets reflecting similar phenomena. Referring to these findings, equation (18) is the probability function (logit model) of free relative care, where $\boldsymbol{Z}$ is a vector of household characteristics, including education and race.

$$Pr_r^{free}(\boldsymbol{I}_r^{free} = 1|\boldsymbol{Z}) = \frac{1}{1 + e^{-(\delta_{r0}^{free} + \boldsymbol{Z}'\boldsymbol{\delta}_r^{free})}} \tag{18}$$

All the above information is known to the household before any decisions.

3.4 Household's Problem

Based on all the information above, the household makes maternal labor supply decisions on how much labor to provide L_m and what schedule to work ns_m^{work}. The household makes childcare arrangement decisions on how much paternal care to use τ_f and how to distribute paternal care during nonstandard versus standard hours ns_f^{care}, how much relative care to use in standard and nonstandard hours $\tau_r^{std}\tau_r^{nstd}$, how much provider care to use in standard and nonstandard hours $\tau_p^{std}\tau_p^{nstd}$, which provider to use during standard hours $P^{std} \in \{ps, pa\}$, and whether to use the subsidy I^S to maximize their utility based on all the constraints.

$$
\begin{aligned}
&\max_{\zeta} U(C_{hh}, l_m, l_f, h_1, \tau_{parent}, \zeta | \text{age, edu, race, Y}, \Phi) \\
&s.t. \qquad \text{Time constraints: equations (1)-(8)} \\
&\qquad\qquad \text{Budget constraint: equation (9)} \\
&\qquad\qquad \text{Skill production technology: equation (12)}
\end{aligned}
$$

where choice set $\zeta \equiv \{L_m, ns_m^{work}, \tau_f, ns_f^{care}, \tau_r^{std}, \tau_r^{nstd}, \tau_p^{std}, \tau_p^{nstd}, P^{std}, I^S\}$. According to the timing of the model, the household starts with the information set

$$
\Phi = \{h_0, \epsilon_h, \epsilon_w, \epsilon_{parent}^q, I_r^{available}, I_r^{free}, I_r^{nstd}, \epsilon_r^q, \epsilon_r^p, \epsilon_{ps}^q, \epsilon_{ps}^p, \epsilon_{pa}^q, \epsilon_{pa}^p, E^s, E^{hs}\},
$$

and make decisions based on the revealed information. The model is solved using a mixed numerical and analytic solution, and the parameters are estimated using the GMM method. The computational details are in the Appendix D.

4 Data

This paper focuses on families with young children aged four and younger. The three main data sets used in this paper are the National Survey of Early Care and Education (NSECE) 2019 data, the National Longitudinal Survey of Youth - 1997 Cohort (NLSY97) data, and the Early Childhood Longitudinal Study-Birth Cohort (ECLS-B) data. The NSECE data provides detailed weekly calendar information on work and care arrangement; the NLSY97 data facilitates analyzing how work schedules could potentially affect workers' wages; and the ECLS-B data provides supportive information on qualities of different types of care, how price and quality are correlated, and measurement of children's skills. The American Time Use Survey (ATUS) 2017-2018 data and the Current Population Survey (CPS) 1985 1991, 1997, 2001, and 2004 data are used to demonstrate the representativeness of the NSECE and NLSY data regarding the schedule information and provide other supplemental information.

4.1 The NSECE Data – Work and Care Calendar Information

The NSECE data is a nationally representative cross-sectional data collected in 2012 and 2019 and contains detailed work and care schedule data, and other provider information. Analyses in this paper use the most recent survey from 2019. Schedule-related information in NSECE is essential for the analysis in this paper since standard and nonstandard working and caring schedules are the key features that separate this paper from other structural papers. In the household calendar data, a calendar week comprises 672 slots of 15-minute duration, which provides detailed information about how the households arranged their time during the past week. In this paper, I define standard hours as hours from 8 a.m. to 6 p.m. Monday through Friday. Table 1 shows the summary statistics for the NSECE 2019 data.

The NSECE survey questions only asked about schedule arrangements in the '*past week*', and the interviews were mainly completed during the first half of the year. These raise concerns that the fluctuation in the "*past week*" might be more significant than the fluctuation in a "*usual week*" and that the schedule in the first half of the year might differ from the schedule over the year. In Appendix H, I resolve these concerns using the American Time Use Survey (ATUS) 2017-2018 data, which is another nationally representative time diary survey data collected over the year and asked questions of the usual week, like "*type of schedule usually worked*". The comparison between the NSECE data and the ATUS data indicates that workers' behaviors regarding schedules and work hours exhibit consistency across these two datasets. The reason for using the NSECE data but not the ATUS data as the primary data set is that the NSECE data contains more detailed schedule information over the whole week.

4.2 The NLSY97 Data – Longitudinal Schedule and Wage

The NLSY97 is a nationally longitudinal project that follows a representative sample of American youth born from 1980 through 1984. In the initial survey in 1997, the ages of participants ranged from 12 to 16. This is an annual survey from 1997 to 2011 and a biannual survey afterward. This paper uses all the records from Round 1 (1997-1998) through Round 19 (2019-2020) and only focuses on the periods after the participant's age is above 18.

This data set contains extensive information on respondents' labor market behavior. It expressly provides longitudinal work schedule information, which is rarely included in other data sets and is vital in consistently estimating the model's wage function.

The key variable, the nonstandard fraction of work hours ns^{work}, is defined using the following survey question. Ideally, with detailed calendar information, standard hours are defined as from 8 a.m. to 6 p.m. Monday through Friday, as I have done to the NSECE

Table 1: NSECE 2019, Summary Statistics Conditional on with Young Child

Variable	N	Mean	SD	Min	Max
mom age*	5720	32.12	5.76	18	50
dad age	4565	34.22	6.51	18	70
I(R White)	5737	0.66	0.47	0	1
I(R Black)	5737	0.12	0.32	0	1
I(R other)	5737	0.22	0.41	0	1
I(mom no college)**	5553	0.30	0.46	0	1
I(mom some college)	5553	0.30	0.46	0	1
I(mom bachelor+)	5553	0.40	0.49	0	1
child age	5908	2.54	1.41	0	4.92
number of child ages btw 0-4	5908	1.52	0.65	1	5
number of child ages btw 5-17	5908	0.82	1.07	0	7
mom hourly wage***	2251	22.85	15.05	7.25	90.14
mom working hours | hrs>0	2756	34.18	14.09	0.5	60
mom nonstandard frac of working hours****	2856	0.21	0.28	0	1
dad hourly wage	2647	27.25	15.85	7.25	105.80
dad working hours | hrs > 0	3720	46.82	13.49	1	84
dad nonstandard frac of working hours	3788	0.22	0.24	0	1
household income(k)	5794	73.11	57.65	1.20	293.30
I(relative available for care)	5787	0.54	0.50	0	1
I(use relative care)	5908	0.25	0.43	0	1
I(use provider care)	5908	0.40	0.49	0	1
hours of relative care	5849	6.84	15.07	0	84
hours of provider care	5849	11.49	17.69	0	65
hours of relative care | hrs>0	1461	28.07	18.33	0.25	84
hours of provider care | hrs>0	2034	29.56	16.45	0.25	65

Source: The NSECE 2019 Household Survey data.

* Only households whose mothers are between 18 and 50 and whose fathers are above 18 are included in the analysis. For single-parent families, this restriction is imposed on the parent who presents.

** Father's education is unobservable in the NSECE data.

*** Hourly wage is constrained to be above 7.25.

**** Since NSECE contains detailed calendar information, standard hours are defined as from 8 a.m. to 6 p.m. Monday to Friday.

data. The NLSY data only provides a rough measurement of the work schedule, and I approximate the nonstandard fraction of working hours consistent with the detail work calendar case. If the respondent reports he/she works a "*regular day shift*", the nonstandard fraction of work hours is defined as 0; if the respondent reports "*shift rotates*" or "*split shift*", the nonstandard fraction of work hours is defined as 0.5; for all the other cases like "*regular evening shift*", "*regular night shift*", "*irregular schedule or hours*", and "*weekends*", the nonstandard fraction of work hours is defined as 1. More details are presented in Table 2.

There are several reasons why the variable should be defined as a continuous variable instead of an indicator that reflects whether the respondent works a nonstandard schedule. First, defining the variable as a continuous variable allows non-linearity between earnings and working hours and between hourly wage and working hours, which exists in the data and has been revealed and argued in Goldin [2014] and Bick et al. [2022]. Next, the detailed calendar information in the NSECE data reveals that the distribution of the nonstandard fraction of work and care hours is smooth and has no spike between zero and one. This distribution is included in Appendix B.1 Figure 4. This implicitly reveals that work and care schedules are more complicated than just binary, and treating them as continuous variables may help us better understand household behaviors.

To provide more convincing evidence that this way of defining the schedule provides representative information about the actual work calendar. I compare schedules reported in the NLSY97 data with detailed and rough schedules reported in other data sets: the CPS Supplements–Work Schedules (1985 1991 1997 2001 2004) data, the NSECE 2019 data, and the ATUS 2017-18. Detailed tables are presented in Appendix H.2. All the data sets show consistent data patterns.

Table 3 presents the pooled summary statistics for this data set and Table 4 shows the summary statistics based on respondents' age and based on survey year.

4.3 The ECLS-B Data – Skill and Care Quality Information

The restricted ECLS-B data, as a nationally representative longitudinal data for young children, followed 10,700 participating children born in 2001 from birth through kindergarten entry. Specifically, surveys were carried out when children were approximately nine months old (2001-02), two years old (2003-04), and four years old/preschool age (2005-06). Additionally, kindergarten child assessment data were collected in the 2006-07 wave.

This data set provides information about childcare quality and children's skills. It also records other childcare information, which together helps identify the quality distribution,

Table 2: Definition and distribution of standard fraction of working hours

fraction of nonstandard working hours among total working hours $\mathbf{ns^{work}}$ is defined as	Survey Question: Which of the following categories best describes the type of schedule you (work/worked) for this employer (at this time/that time when you left)?	Freq.	Percent
0	regular day shift	63,462	56.94
1	regular evening shift	13,529	12.14
1	regular night shift	7,399	6.64
0.5	shift rotates (changes periodically from days to evenings or nights)	13,886	12.46
0.5	split shift (consists of two distinct periods each day)	2,848	2.56
1	irregular schedule or hours	10,148	9.1
1	weekends	184	0.17
	Total	111,456	100

Source: NLSY97 round 1 (1997-98) through round 19 (2019-20).

Note: Universe: R $\geq$ 18; has work schedule information; has valid employer; not military; job last at least 13+ weeks; job last 2+ weeks since date of last interview; not self-employed; works more than 35 hours per week.

Table 3: NLSY97, Summary Statistics (pooled)

Variable	N	Mean	SD	Min	Max
age	109,602	25.49	5.38	18	40
$\mathbf{I}$(male)	109,602	0.49	0.50	0	1
$\mathbf{I}$(no college)	109,602	0.49	0.50	0	1
$\mathbf{I}$(some college)	109,602	0.30	0.46	0	1
$\mathbf{I}$(bachelor+)	109,602	0.21	0.41	0	1
$\mathbf{I}$(married)	109,393	0.24	0.43	0	1
number of children	109,602	0.66	1.05	0	12
hours worked	106,218	33.46	11.95	3	60
hourly base wage w^b_{ijt} *	103,598	15.63	8.32	3.07	55.65
hourly wage with compensation w_{ijt} *	100,811	17.13	9.39	5.24	64.69
$\log w_{ijt} - \log w^b_{ijt}$ *	100,218	0.07	0.18	0	1.35
$\mathbf{I}(\text{fulltime})_{ijt}$ **	108,569	0.59	0.49	0	1
$\mathbf{I}(\text{overtime})_{ijt}$	108,569	0.12	0.32	0	1
ns^{work}_{ijt} ***	109,602	0.36	0.44	0	1

Source: NLSY97 round 1 (1997-98) through round 19 (2019-20). Tabulate workers age above 18 and with work schedule information.

* Hourly wage is in 2019 dollars.

** This indicator equals one if hours worked at the main job are over 35 hours.

*** This variable is defined as the fraction of nonstandard hours over total working hours. For surveys years before 2013, the variable was created for each job lasting 13 weeks or more; for surveys years 2013 to present, the variable is created for each job lasting 26 weeks or more.

Table 4: NLSY97, Summary Statistics Based on Age or Year

	for Respondents Age 25					for Year 2019				
Variable	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
age	7,430	25.00	0.00	25	25	5,523	36.83	1.45	34	40
I(male)	7,430	0.49	0.50	0	1	5,523	0.49	0.50	0	1
I(no college)	7,430	0.43	0.49	0	1	5,523	0.42	0.49	0	1
I(some college)	7,430	0.27	0.45	0	1	5,523	0.28	0.45	0	1
I(bachelor+)	7,430	0.30	0.46	0	1	5,523	0.30	0.46	0	1
I(married)	7,420	0.25	0.44	0	1	5,496	0.48	0.50	0	1
number of children	7,430	0.60	0.93	0	6	5,523	1.46	1.30	0	10
hours worked	7,235	35.22	11.15	3	60	5,338	38.16	10.40	3	60
hourly base wage w^b_{ijt} *	7,072	15.94	7.35	3.08	55.43	5,021	22.80	11.04	3.17	55.56
hourly wage with compensation w_{ijt} *	6,914	17.43	8.30	5.24	64.02	4,918	24.97	12.56	5.3	64.69
$\log w_{ijt} - \log w^b_{ijt}$ *	6,842	0.07	0.19	0	1.34	5,084	0.06	0.15	0	1.34
I(fulltime)$_{ijt}$ **	7,388	0.67	0.47	0	1	5,483	0.78	0.41	0	1
I(overtime)$_{ijt}$	7,388	0.13	0.33	0	1	5,483	0.22	0.41	0	1
ns^{work}_{ijt} ***	7,430	0.33	0.44	0	1	5,523	0.21	0.35	0	1

Source: NLSY97 round 1 (1997-98) through round 19 (2019-20). Tabulate workers age above 18 and with work schedule information.

* Hourly wage is in 2019 dollars.

** This indicator equals one if hours worked at the main job are over 35 hours.

*** This variable is defined as the fraction of nonstandard hours over total working hours. For surveys years before 2013, the variable was created for each job lasting 13 weeks or more; for surveys years 2013 to present, the variable is created for each job lasting 26 weeks or more.

the correlation between quality and price, the skill production function, etc.

Child's skills are measured through three main aspects: cognitive skill, physical skill, and socio-emotional skill, which are evaluated by multiple measurements, including the Bayley Short Form-Research Edition (BSF-R), ECLS-B Cognitive and Physical Assessment Battery, Nursing Child Assessment Teaching Scale (NCATS), and Two Bags Task. Not all the measurements are surveyed in each wave as presented in Table 5, and each has more granular sub-measurements. For instance, the Bayley Short Form-Research Edition (BSF-R) is only surveyed in wave 1 and wave 2 and includes two scales: the mental scale, which is designed to assess early cognitive and language skills, and the motor scale, which is designed to assess fine and motor abilities. Since BSF-R is the only cognitive measurement in wave 1, the sum of standardized, more granular BSF-R sub-measurements is considered as the initial cognitive score. Aggregated skill scores are equal to the sum of standardized cognitive, physical, and socio-emotional scores. Cognitive, physical, and socio-emotional scores are calculated as the sum of standardized sub-measurements. Aggregated skill scores are further standardized based on survey waves. In this paper, I use the aggregate skill at wave 1, when the child is around nine months old, as the measure of $\ln h_0$. I use the aggregate skill at wave 4, when the child is around five years old, as the measure of $\ln h_1$.

To measure the quality of provider and relative care, I use the observer-based Arnett Scale of Caregiver Interaction Scale (Arnett [1989]). This measurement is widely used to

Table 5: Skill Measurements

Domain	Instrument	Content	wave 1 9-month	wave 2 2-years	wave 3 preschool	wave 4 kindergarten 2006 wave
Cognitive	Bayley Short Form-Research Edition (BSF-R) Mental	General mental ability, including problem solving and language acquisition	x	x		
	ECLS-B Cognitive Assessment Battery	Early reading			x	x
		Mathematics			x	x
Physical	Bayley Short Form-Research Edition (BSF-R) Motor	Fine motor skills	x	x		
		Gross motor skills	x	x		
	ECLS-B Physical Assessment Battery	Fine motor skills			x	x
		Gross motor skills			x	x
Socio-emotional	Nursing Child Assessment Teaching Scale (NCATS)	Child's clarity of cues and responsiveness to parent	x			
	Two Bags Task	Child's clarity of cues and responsiveness to parent		x	x	

Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

evaluate the interaction between caregiver and child and allows me to compare childcare quality among different providers.

To measure quality differences in standard and nonstandard hours, I use the survey question, which asked the provider about the provision of care during nontraditional hours, such as during the evening, overnight, or on weekends. The answer is binary. One limitation of this variable is that it was only asked in wave 2 when the child was around two years old. To use this information, I assume that providers who provide service to the 2-year-old child are representative of providers who serve children below five.

Parental care quality is measured by questions from the Short Form of the Home Observation for Measurement of the Environment(HOME) scale (Bradley and Caldwell [2000], Bradley and Caldwell [1984], Bradley and Caldwell [1979]) in the ECLS-B data. This commonly used HOME scale evaluates the home environment of the child. To capture parental quality, I measure it using the mean of the frequencies that the parents read to the child, tell stories to the child, and sing songs with the child in a typical week.

All the skills, non-parental care quality, and parental care quality are standardized based on the survey year, which is also roughly the age of the child. The units for these variables are the standard deviation in that survey year (or roughly at that age). The summary statistics for ECLS-B wave 1 through wave 3 data are presented in Table 6. This table shows that only around 16% of the providers used by the households report provision of care during nontraditional hours, while approximately 67% of the relatives used by the households report provision of care during nontraditional hours. This is consistent with what is revealed using the NSECE 2019 data, which shows that compared with formal providers, relatives are more likely to be available during nontraditional hours and are more likely to be free of

Table 6: Summary Statistics - ECLS-B Data (Wave 1-3)

	N	Mean	SD	Min	Max
Household Characteristics					
mom age	27300	29.21	6.07	18.00	50.00
dad age	24000	32.09	6.64	18.00	62.00
I(dad white)	26400	0.83	0.38	0.00	1.00
I(dad black)	26400	0.13	0.33	0.00	1.00
I(dad other)	26400	0.04	0.21	0.00	1.00
I(mom white)	30450	0.81	0.39	0.00	1.00
I(mom black)	30450	0.14	0.35	0.00	1.00
I(mom other)	30450	0.04	0.21	0.00	1.00
I(mom no college)	30700	0.36	0.48	0.00	1.00
I(mom some college)	30700	0.34	0.48	0.00	1.00
I(mom bachelor +)	30700	0.29	0.45	0.00	1.00
I(married)	27950	0.70	0.46	0.00	1.00
household income(k, 2019 \$)*	28200	76.44	64.42	3.27	288.65
Childcare Arrangement					
I(use relative care)	28150	0.23	0.42	0.00	1.00
I(use provider care)	30550	0.39	0.49	0.00	1.00
parental hours	30550	71.43	18.92	7.50	87.50
hours of relative care	28150	5.97	13.58	0.00	80.00
hours of provider care	30550	10.52	15.99	0.00	60.00
hours of relative care $\vert hrs > 0$	6700	26.15	16.74	1.00	80.00
hours of provider care $\vert hrs > 0$	11750	26.78	14.69	1.00	60.00
I(relative care operate nontraditional hours)	1150	0.67	0.47	0.00	1.00
I(provider care operate nontraditional hours)	1850	0.16	0.37	0.00	1.00
Quality**					
quality of parental care	28200	0.00	1.00	-8.58	4.24
quality of relative care	600	-0.16	0.98	-5.32	1.60
quality of provider care	2350	0.05	1.00	-5.03	1.60
Hourly Price					
I(relative free of charge)	6750	0.73	0.45	0.00	1.00
I(provider free of charge)	10800	0.14	0.34	0.00	1.00
hourly price for relative care (2019\$)	6500	0.87	1.95	0.00	12.63
hourly price for provider care (2019\$)	10100	5.03	4.83	0.00	30.31
hourly price for relative care (2019\$) $\vert > 0$	1550	3.51	2.46	0.09	12.63
hourly price for provider care (2019\$) $\vert > 0$	8450	5.89	4.72	0.03	30.31
Skill***					
initial skill	9800	0.00	1.00	-5.05	4.18
end skill	6600	0.00	1.00	-3.76	2.38

Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Notes: Sample sizes are rounded to the nearest 50. All statistics use sampling weights provided by the ECLS-B.

* Household income is capped at 200k in each wave and is inflated to 2019 dollars.

** Quality of parental care is measured based on the Short Form of the Home Observation for Measurement of the Environment(HOME) scale and is standardized based on the survey year. Quality of nonparental care is measured using the Arnett Scale of Caregiver Interaction Scale (Arnett 1989) and is standardized based on the survey year.

*** Skills are evaluated by multiple measurements, including Bayley Short Form-Research Edition (BSF-R), ECLS-B Cognitive and Physical Assessment Battery, Nursing Child Assessment Teaching Scale (NCATS), and Two Bags Task and are standardized based on survey year.

charge.

5 Estimation

The structural model is estimated using three steps. As is pointed out by Lavetti [2023], the estimation of compensating wage differentials has multiple empirical challenges and is usually difficult to estimate. Estimates of wage differentials were often incorrectly signed or insignificant due to various reasons, such as the omission of vital worker ability dimensions, the omission of job characteristics, and imprecise measurement of job characteristics. Rosen [1986]. In the first step, I use the NLSY97 data with instrumental variables and fixed effects to address these concerns and estimate the wage function outside the model. In the second step, I calibrate the subsidy policy parameters from the existing literature and estimate the functions without endogeneity concerns outside the model. Lastly, conditional on parameters calibrated and estimated outside of the model, I estimate the rest of the parameters within the model using the simulated method of moments (SMM).

5.1 Identification of the Wage Function

The main goal of this section is to obtain consistent estimates for all the wage parameters in the model. Regressions are run separately for males and females, which allows males and females to have different wage parameters, which could originate from heterogeneous comparative advantages in various jobs.

5.1.1 Potential Bias

Suppose the true wage data generating process (DGP) is as shown in equation (19), where w_{ijt} denotes hourly wage including all extra monetary compensation including overtime, tips, commissions, bonuses, incentive pay, etc., for individual i with job j at time t. Suppose w_{ijt} can be decomposed as base rate w^b_{ijt} and all other monetary compensation w^c_{ijt}, $w_{ijt} \equiv w^b_{ijt} * w^c_{ijt}$.[18] Wage base rate w^b_{ijt} depends on controls X_{ijt}. Other compensation w^c_{ijt} depends on both controls X_{ijt} and the worker's work schedule, which is defined as the fraction of nonstandard working hours among total working hours ns^{work}_{ijt}. $\alpha^{edu}_w \equiv \Sigma_e I(edu_{it} = e)\alpha^e_w$

[18] In this paper monetary compensation other than base rate is considered as an additional percentage of hourly base rate. Take the Fair Labor Standards Act (FLSA) regulated overtime pay for instance, though overtime is not equivalent to a nonstandard schedule. The FLSA mandates that covered nonexempt employees must be paid one and a half times their regular pay for overtime hours worked. Suppose a worker works hrs hours, the hourly wage after compensation is then $w = \frac{40w^b+1.5(hr-40)w^b}{hrs} = w^b(1.5 - \frac{20}{hrs})$.

reflects that in reality, schedule premium for working nonstandard schedule can potentially vary across education group.[19]

$$\log w_{ijt} \equiv \log(w^b_{ijt} w^c_{ijt}) = \underbrace{X'_{ijt}\beta^b + \xi^b_{ijt}}_{\log w^b_{ijt}} + \underbrace{\alpha^{edu}_w ns^{work}_{ijt} + X'_{ijt}\beta^c + \xi^c_{ijt}}_{\log w^c_{ijt}}$$
$$= \alpha^{edu}_w ns^{work}_{ijt} + X'_{ijt}\beta + \xi_{ijt} \tag{19}$$

Lavetti [2023] points out that there are several empirical challenges when estimating compensating wage differentials. Bias in the estimation can come from imperfect competition and friction in the labor market. For instance, certain jobs with both better schedules and higher wages might not be obtained due to the friction.

Bias can come from the trade-off between income and substitution effect. Workers' schedule choices are partly explained by self-selection (Kostiuk [1990], Lanfranchi et al. [2002]). For instance, conditional on all else being equal, workers who are lucky and with higher base rates (higher ξ^b_{ijt}) might be more likely to choose not to work in a nonstandard schedule. In comparison, workers who are unlucky and with lower base rates (lower ξ^b_{ijt}) might be more likely to choose to work more and work in the nonstandard schedule to gain schedule compensation. If this is true, it is expected that in some cases, nonstandard work schedules could be associated with lower wages w_{ijt}. In other words, ξ^b_{ijt} should be controlled for but couldn't be due to non-observability.

Bias can also come from unobserved variables, such as ability, work habits, perseverance, etc. As shown in equation (19), without explicitly modeling other individual characteristics that affect wages, they are included in the error term and bias the estimates. For instance, suppose working standard hours is commonly preferred by all the workers; workers with higher abilities are sorted to work lower fractions of nonstandard hours among total working hours and are also more likely to have higher wages. Under this situation, not controlling for individual fixed effects biases schedule premiums downward.

Additionally, the survey data usually lacks a good measurement of the worker's schedule, and the measurement error biases the estimate toward zero.

5.1.2 Resolving the Biases

In this section, I use the abundant information provided by the NLSY97 panel data, rounds 1-19 (1997-2019), to solve the biases mentioned above. Information about main wage rate w^b_{ijt},

[19] The wage function in this paper allows non-linearity between hourly wage and working hours and between annual earnings and working hours, which is inspired by Goldin [2014]. Based on the setting of the wage function in this paper and depending on the value of α^{edu}_w, when α^{edu}_w equals zero and with everything else being equal, the hourly wage is constant with working hours; when α^{edu}_w is none zero, non-linearity emerges.

and wage rate with extra monetary compensation w_{ijt} are collected based on the following survey questions interviewed in the NLSY97 data.[20]

Table 7: Main survey questions about wages

1. *Did you usually receive overtime pay, tips, commissions, or bonuses when you started with this employer?*
2. *About how much income did you usually receive from [compensation: overtime, tips, commissions, bonuses, incentives]? [Obtain time unit and $ amount.]*
3. *Excluding overtime pay, tips, commissions, bonuses, and incentive pay, what is R's rate of earnings on this job? [Obtain time unit and $ amount.]*
...

The main wage rate w^b_{ijt} is derived from the third question, and the wage rate with extra monetary compensation w_{ijt} (e.g., overtime, tips, commissions, bonuses, incentive pay, other pay) are derived from the second and third questions. To address the biases arising from search friction and the trade-off between income and substitution effects previously discussed, $cov(ns^{work}_{ijt}, \xi^b_{ijt}) \neq 0$, I take the difference between the wage with additional compensation and the base wage rate, $\log w_{ijt} - \log w^b_{ijt}$, using it as the dependent variable.[21] This approach facilitates comparisons within a given job and effectively eliminates the influence of base wage rate shocks on schedule choices.

Targeting the bias from unobserved variables, I use the abundant information collected in the NLSY97 panel data and control for age, age square, fulltime indicator, overtime indicator, education fixed effects, year fixed effects, and especially individual×job fixed effects, $X_{ijt} \equiv \{age_{it}, age^2_{it}, fulltime_{ijt}, overtime_{ijt}, edu_{it}, year_t, \phi_{i,j}\}$.

Additionally, I construct an instrument to solve the potential measurement error. As is presented in the Data Section 4, the NLSY97 survey data collects schedule information through the following question "*Which of the following categories best describes the type of schedule you (work/worked) for this employer (at this time/that time when you left)?*". Choices can be "*regular day shift*", "*regular evening shift*", "*regular night shift*", etc. I map the survey question to ns^{work} in the model, defined as the fraction of nonstandard working hours among total working hours. Measurement error can come from the following aspects. First, suppose the true fraction of nonstandard working hours among total working hours is

[20] How wage is reported in the survey: https://nlsinfo.org/content/cohorts/nlsy97/topical-guide/employment/wages.

[21] In reality, the additional compensation could be a fraction of the base rate or a flat rate, and I am modeling it as a fraction of the base rate. Additionally, using the difference of log instead of log difference also avoids log0.

a continuous variable ranging from zero to one. However, there are only a limited number of options for respondents to answer the survey question. The mapping of the true schedule to the survey options is unclear, and "*regular*" is a vague definition in precisely depicting the true schedule. For example, suppose a worker works four out of five days a week on the regular day shift but one day not on the day shift. In that case, when answering the question, the worker probably still reports that the best way to describe his/her current job is "*regular day shift*"; however, the additional nonstandard hours contribute to the increase in the bonus. Second, for each respondent, the survey is asked at one point of the year, which may not be representative enough to describe the schedule of the current job, and answers may vary if the question is asked at a different time of the year. For instance, answers from an accountant might be different at the end of the year compared with the middle of the year. Third, though the ideal data should record the real-time wage difference and schedule change, in the survey, the unit of around 20-30% of the reported earnings is annual earning, the time range of which might be too rough to capture the real-time co-movement between schedule and wage change. Last, my way of mapping the survey question to the fraction of nonstandard working hours among total working hours adds additional measurement errors.

To solve the attenuation bias caused by measurement errors, I construct the instrumental variable in the following way. For worker i who works in job j at year t, from the data I can observe the worker's occupation *occ(ijt)*. I take the average of the reported schedule from all other workers excluding worker i who work in the same occupation at time t as another measurement for worker i's actual work schedule at job j in year t.[22] Since the respondent is interviewed in different months over the year, I use this measurement to approximate the true schedule over the year.

$$ns^{work}_{occ(ijt),t} = \frac{\Sigma_{\iota \neq i}\{\big(occ(\iota jt) = occ(ijt)\big) ns^{work}_{\iota jt}\}}{\Sigma_{\iota \neq i}\big(occ(\iota jt) = occ(ijt)\big)} \tag{20}$$

Suppose the true schedule for worker i in job j at time t is ns^{*work}_{ijt}, which is a value between zero and one, I assume the measurement error is uncorrelated with the true schedule, $\mathrm{E}[\mu_{ijt}|ns^{*work}_{ijt}] = 0$ and $\mathrm{E}[\nu_{ijt}|ns^{*work}_{ijt}] = 0$; and assume the measurement errors are independent with each other $cov(\mu_{ijt}, \nu_{ijt}) = 0, \forall i, j, t$.

$$ns^{work}_{ijt} = ns^{*work}_{ijt} + \mu_{ijt} \tag{21}$$

$$ns^{work}_{occ(ijt),t} = ns^{*work}_{ijt} + \nu_{ijt} \tag{22}$$

[22] Ideally, I should construct this measurement using all reported schedule information from workers who work in the same occupation at the same firm. However, firms are not observed in the NLSY97 data, and the current measurement is the best that I can construct given limitations of the data.

5.1.3 Wage Function Estimation

Regressions are run separately for males and females. Samples include all the respondents above 18 years old who have valid employers, excluding military jobs and self-employment. I assume mothers and fathers with young children have the same wage function as other workers and assume estimates obtained in this section using NLSY97 data are directly applicable to the model. Regressions are run in two steps; in the first step, I obtain consistent estimates for schedule premium α_w^{edu}, and in the second step, I obtain estimates for the rest of the parameters in the wage function.

Wage Regression – First Step

Table 8 shows the results from the following regression (23), where controls $X_{ijt} \equiv \{age_{it}, age_{it}^2, edu_{it}, fulltime_{ijt}, overtime_{ijt}, year_t, \phi_{i,j}\}$ are gradually added. Column (1) controls for everything in X_{ijt} excluding the individual×job fixed effects $\phi_{i,j}$; column (2) adds individual fixed effects ϕ_i; column (3) adds individual×job fixed effects $\phi_{i,j}$. Column (4)-(6) include all the control variables X_{ijt} and are run using $ns_{occ(ijt),t}^{work}$ as the instrument, where regressions in column (5) and column (6) are run separately for female workers and male workers.

$$\log w_{ijt} - \log w_{ijt}^b = \underbrace{\alpha_w^{edu} ns_{ijt}^{work} + X_{ijt}'\beta^c + \xi_{ijt}^c}_{\log w_{ijt}^c} \tag{23}$$

$$\begin{aligned} ns_{ijt}^{work} &= ns_{ijt}^{*work} + \mu_{ijt} \\ \textbf{IV}: \quad ns_{occ(ijt),t}^{work} &= ns_{ijt}^{*work} + \nu_{ijt} \end{aligned}$$

$$\begin{aligned} \text{where} \quad & \mathrm{E}[\xi_{ijt}^c | ns_{ijt}^{work}, X_{ijt}] = 0, \\ & \mathrm{E}[\mu_{ijt} | ns_{ijt}^{*work}] = 0, \quad \mathrm{E}[\nu_{ijt} | ns_{ijt}^{*work}] = 0, \\ & cov(\mu_{ijt}, \nu_{ijt}) = 0, \forall i, j, t \end{aligned}$$

All else being equal, estimates of α_w^{edu} explain, on average, how much more wages a worker can gain if the worker changes from working in a standard schedule to working in a nonstandard schedule in the current job.

The significant increase in the estimates from column (3) to column (4) implies that the self-reported schedule includes substantial measurement errors. Suppose column (4) reveals the true value of α_w^{edu}, the derived signal-to-noise ratio stands at around 0.03-0.04, with specifics as follows: 0.036 for the group without any college education, 0.040 for the group with some-college experience, and 0.031 for the group with a bachelor's degree or higher.[23]

[23] plim $\widehat{\alpha_w^{edu}} = \alpha_w^{edu}\sigma^2_{ns^{*work}}/(\sigma^2_{ns^{*work}} + \sigma^2_\mu) = \alpha_w^{edu}\frac{1}{1+1/SNR}$, where signal to noise ratio (SNR) $= \frac{\sigma^2_{ns^{*work}}}{\sigma^2_\mu}$.

Table 8: Estimation for schedule compensation

		Dependent Variable: $\log w_{ijt} - \log w^b_{ijt}$					
Independent Variables	parameter	(1)	(2)	(3)	(4) IV	(5) IV female	(6) IV male
ns^{work*}	$\alpha_w^{\text{no college}}$	0.033***	0.028***	0.005*	0.143**	0.223***	0.073
		(0.002)	(0.002)	(0.003)	(0.057)	(0.081)	(0.081)
	$\alpha_w^{\text{some college}}$	0.046***	0.041***	0.005*	0.131**	0.208***	0.054
		(0.003)	(0.004)	(0.003)	(0.052)	(0.075)	(0.073)
	$\alpha_w^{\text{bachelor +}}$	0.032***	0.035***	0.003	0.100**	0.159**	0.038
		(0.003)	(0.005)	(0.004)	(0.050)	(0.072)	(0.071)
Controls		$constant, age_{it}, age^2_{ijt}, fulltime_{ijt}, overtime_{ijt}, edu_{it}, year_t$					
Additional FE		None	ϕ_i	$\phi_{i,j}$	$\phi_{i,j}$	$\phi_{i,j}$	$\phi_{i,j}$
Obs		100,169	99,860	76,557	75,499	38,490	37,009
Individuals		8,594	8,253	7,716	7,692	3,812	3,880

Source: NLSY97 round 1 (1997-98) through round 19 (2019-20), conditional on respondent ages above 18 years old; has valid employer; not military; jobs last more than 13 weeks if before the year 2013 or jobs last more than 26 weeks if after the year 2013.

* Hourly wage $\log w_{ijt}$ includes all extra compensation such as overtime, tips, bonuses, etc.

** Age square is rescaled by 1/100.

Explanations for estimates of α_w^{edu} are as follows. Take female workers without college education for instance; in Table 8 column (5), $\widehat{\alpha}_w^{\text{no college}}$ is interpreted as if a female worker changes from working a full standard schedule to working a full nonstandard schedule, her hourly wage on average increases by around 22.3%. This schedule compensation is around 20.8% for female workers with some college education and around 15.9% for female workers with bachelor's degrees or higher. The results for male workers are comparatively smaller and statistically insignificant. For male workers without college education, such schedule change, on average, increases their hourly wage by around 7.3%. The schedule compensation is 5.4% for male workers with some college education and 3.8% for male workers with bachelor's degrees or higher. The differences in estimated schedule premiums should not be interpreted as wage discrimination. Rather, they may be explained by the comparative advantages of female versus male workers or of those with lower versus higher education across different occupations, resulting in varied occupational distributions.

Wage Regression – Second Step

In the second step, I obtain consistent estimates of the remaining parameters in the wage function. I first estimate the amount of schedule compensation that the worker receives under the current work schedule conditional on the education, $\widehat{\alpha_w^{edu} ns^{work}_{ijt}}$, and then run the following regression in equation (24). Controls X_{ijt} include age_{it}, age^2_{it}, $fulltime_{ijt}$, $overtime_{ijt}$, edu_{it}, $year_t$, $\phi_{i,j}$.

$$\log w_{ijt} - \widehat{\alpha_w^{edu} ns^{work}_{ijt}} = X'_{ijt}\beta + \eta_{ijt} \tag{24}$$

$$\text{where} \quad \eta_{ijt} = (\alpha_w^{edu} - \widehat{\alpha_w^{edu}})ns_{ijt}^{work} + \xi_{ijt}$$
$$\text{and} \quad \mathrm{E}[\eta_{ijt}|X_{ijt}] = 0$$

Table 9 shows results from the second step. One clarification for education fixed effects is that education fixed effects in this regression are only identified by those respondents whose education background historically changed, and individual×job fixed effects absorb part of the effects. The positive estimates for full-time effects and negative estimates for overtime effects on wages are consistent with Bick et al. [2022] that there are wage penalties when working below or above 40 hours.

Table 9: Estimation for other parameters β

	Dependent Variable: $\log w_{ijt} - \widehat{\alpha_w^{edu}} ns_{ijt}^{work}$		
Independent Variables	(1) all	(2) female	(3) male
Age	0.045***	0.066***	0.028*
	(0.011)	(0.015)	(0.015)
Age^{2**}	-0.078***	-0.124***	-0.040
	(0.019)	(0.028)	(0.026)
I(fulltime)	0.042***	0.054***	0.028***
	(0.004)	(0.005)	(0.007)
I(overtime)	-0.033***	-0.040***	-0.030***
	(0.005)	(0.008)	(0.006)
Some college	-0.002	0.006	-0.001
	(0.005)	(0.007)	(0.008)
Bachelor plus	0.076***	0.091***	0.068***
	(0.010)	(0.013)	(0.016)
Other controls		$constant, year_t, \phi_{i,j}$	
Obs	73,628	37,697	35,931
Individuals	7,623	3,787	3,836

Source: NLSY97 round 1 (1997-98) through round 19 (2019-20).
Note: Universe: R $\geq$ 18 has valid employer; not military; job last at least 13+ weeks; job last 2+ weeks since date of last interview; not self-employed.
* ns^{work} is the fraction of nonstandard work hours among total work hours.

I run an additional regression to elaborate on how wage shocks are drawn in the model. After running the regression in equation (24), I estimate $\widehat{\epsilon_{ijt}} \equiv \widehat{\phi_i} + \widehat{\eta_{ijt}}$ and run regression of $\widehat{\epsilon_{ijt}}$ on all the controls excluding individual×job fixed effects, $\{age_{it},\ age_{it}^2,\ fulltime_{ijt},\ overtime_{ijt},\ edu_{it},\ year_t\}$. Wage shocks in the model are drawn based on the results from this regression conditional on the year 2019. Results from this step are shown in Table 10.

5.1.4 Credibility of the Settings and the Estimates

Schedule compensations estimated in this paper are expected to include both direct shift differentials, incentives, or bonuses that are paid for those nontraditional hours. I find that when workers transition from working fully in standard schedules to fully in nonstandard schedules (such as evenings, nights, or weekends), their wages, on average, increase by around

Table 10: Estimation for wage shock in the model

	Dependent Variable: $\widehat{\epsilon_{ijt}}$		
Independent Variables	(1) all	(2) female	(3) male
Age	0.022***	-0.003	0.046***
	(0.006)	(0.008)	(0.008)
Age^{2**}	0.004	0.057***	-0.046***
	(0.011)	(0.014)	(0.015)
$\mathbf{I}$(fulltime)	0.203***	0.158***	0.230***
	(0.003)	(0.004)	(0.005)
$\mathbf{I}$(overtime)	0.088***	0.083***	0.069***
	(0.005)	(0.007)	(0.006)
Some college	0.108***	0.123***	0.112***
	(0.003)	(0.005)	(0.005)
Bachelor plus	0.254***	0.296***	0.246***
	(0.004)	(0.005)	(0.006)
Other controls	$constant, year_t$		
Obs	73,628	37,697	35,931
Individuals	8,594	4,199	4,395

Source: NLSY97 round 1 (1997-98) through round 19 (2019-20).
Note: Universe: R $\geq$ 18 has valid employer; not military; job last at least 13+ weeks; job last 2+ weeks since date of last interview; not self-employed.

* ns^{work} is the fraction of nonstandard work hours among total work hours.

10%-14.3%, depending on their education levels. When this analysis is applied separately to female and male workers, it shows that if a female worker (or a male worker) switches from working fully in standard schedules to fully in nonstandard schedules, on average, her (or his) hourly wage increases by 15.9% - 22.3% (or 3.8% - 7.3%), depending on their education level.

Results in this paper are comparable with estimates from other papers. Kostiuk [1990] focused on male manufacturing workers in the Current Population Survey (CPS) data and estimated the average shift premium to be 8.2%. It found that union workers had a relatively higher premium at 18.2% compared to non-union workers at 5.3%. Using CPS data, Schumacher and Hirsch [1997] attempts to understand the wage gap between registered nurses (RNs) working in hospitals and those working outside of hospitals. The study documents that the evening shift differential for RNs is approximately 4%, and the night shift differential is around 11.6%, which accounts for 10% of the wage difference between hospital and non-hospital RNs. Using French data, Lanfranchi et al. [2002] finds that shift premium is around 16% for full-time blue-collar workers. Through the analysis of a nationwide field experiment, Mas and Pallais [2017] estimates jobseekers' willingness to pay for various work schedule arrangements. From their analysis, on average, workers demand a 14% premium for working evenings and a 19% premium for working weekends in terms of schedule differentials.

5.2 Calibrated Parameters and Exogenous Functions Estimation

Under the Child Care and Development Block Grant (CCDBG), the main federal program that aims to assist with childcare, there are state-level variations within the framework of federal guidelines. Based on Schulman [2019], in 2019, parent monthly copayments for a three-member household with an income at 150% of the poverty level and one child in care varies from 0% (South Dakota) to 22% (Hawaii) of income across states. The income eligibility threshold varies from 124% (Indiana) to 292% (Vermont) federal poverty level. In this paper, childcare subsidy parameters are calibrated from the nationwide population-weighted averages across states. In the model, copayment ψ is set to be 7.2%, which is the nationwide average level of copayment in 2019; and income eligibility threshold $\bar{y}^s$ is set as 188% the federal poverty level, which is the nationwide average level of income eligibility threshold. Calibrated from Griffen [2019], rate ceiling rc is set to be \$5.27 [24] and offer probability index intercept γ_0^s is set to be -0.86, which means approximately 30% of the eligible households actually have access to the subsidies.

In the NSECE 2019 data, all respondents were asked whether there were relatives of any child who lived nearby within 45 minutes of the household. If so, whether any of these relatives were willing to care for children in the household regularly. If the respondent had positive answers to both questions, I define relative availability indicator $\mathbf{I}_r^{available}$ as one, meaning that there are relatives nearby and willing to help take care of the child. The relative availability function is estimated outside of the model using this information provided in NSECE 2019 data. The distribution of parental care is also estimated outside of the model using ECLS-B data because parental care is almost always utilized, and there is no obvious reason that the missing parental care quality is caused by selection.

5.3 SMM Estimation

5.3.1 Algorithm and Identification

Conditional on all the parameters obtained outside of the model, I estimate the rest of the parameters within the model using the simulated method of moments (Gourieroux et al. [1993]) with data from the Early Childhood Longitudinal Study-Birth Cohort (ECLS-B) and the National Survey of Early Care and Education (NSECE). Estimates are defined in the following way

$$\hat{\theta} \equiv \text{argmin}_\theta \big[\beta^{Data} - \hat{\beta}(\theta)\big]' W^{Data} \big[\beta^{Data} - \hat{\beta}(\theta)\big] \tag{25}$$

[24] Rate ceiling has been adjusted to be in 2019 dollars.

where θ is the vector of parameters that need to be estimated from the model, β^{Data} is the vector of moments from the data, $\hat{\beta}(\theta)$ is the vector of moments simulated conditional on parameters θ, and W^{Data} is the weighting matrix. For my estimates, I use the diagonal matrix with inverse variance as the weight and additional weights are given to some key moments.

Moments are selected to identify these parameters. In total, around four hundred moments are used to estimate 50 parameters within the model. These moments include the proportion of free relative care, care prices by different types of care providers (including relatives, providers who offer services only during the standard schedule, and providers who offer services during any schedule), revealed care quality from different types of providers, usage of care, and maternal labor supply; as well as moments by education groups, by race groups, and by marital status. Some supplemental regression estimates are also used as moments for indirect inference purposes. For instance, regressions include regression for skill production functions, regression for quality distributions, and regression for price functions. Identification of certain parameters is elaborated more in Appendix F. Identification graphs for each parameter are presented in Appendix F.2.

6 Estimation Results and Model Fit

6.1 Estimation Results

Table 11 lists the parameters estimated outside of the model and Table 12 presents the rest of the parameters estimated within the model. The results show that, on average, providers who provide care during any schedule, both standard and nonstandard hours, are of significantly lower quality compared to relatives and standard-hour-only providers. For the base group of households (white and no college education), the average quality for relative care is around -1.11 (γ_{r0}) standard deviations lower than the average non-parental care quality, average quality for standard-hour-only providers is around -0.80 (γ_{ps0}) standard deviations lower, and average quality for any-schedule providers is around -2.11 (γ_{pa0}) standard deviations lower.[25] Quality of Head Start programs on average is 0.326 (γ_{hs}) standard deviation higher than all non-parental care quality. Lower educated households are more likely to be provided with free relative care, and relative care is predicted to be accessible during nonstandard

[25]For the base subgroup of households, on average, quality of any-schedule providers is around 1.3 standard deviations lower than the quality of standard-hour-only providers. Similar facts are revealed in other subgroups of households, as is shown in Appendix E Table 25, that the quality of any-schedule providers is, on average, 1.158 standard deviations lower than the quality of standard-hour-only providers.

hours with probability 0.53 (Pr_r^{nstd}). As for policy-relevant parameters, the estimates reveal that the Head Start program is rationed. Conditional on household income being below the poverty line, around 66%[26] of households have access to the program. Achieved enrollment could be lower, and households in the model could choose not to enroll in the Head Start program even though they have access to it by not using the granted provider.

Conditional on quality being the standardized mean quality, the average price for providers operating during any schedule is slightly lower than that for those operating during only the standard schedule. However, prices for providers operating under any schedule are more sensitive to quality than those exclusively offering the standard schedule; when quality increases by one standard deviation, the price increases by 14.5% (β_{pa1}) for providers available in any schedule and increase by around 5.9% (β_{ps1}) for providers only available in the standard schedule.

Estimated parameters in the skill production function reflect the productivity of different types of care in producing child skills at age 5. I estimate that parental care is more productive for the skill development of a child whose initial skill is above the median, and non-parental care, relative care, and provider care are more productive for the skill development of a child whose initial skill is below the median. Caution is needed when interpreting these results. Since the quality of parental care and the quality of non-parental care are assessed with different measurements and are separately standardized to be with mean zero and standard deviation one, the productivity of parental and non-parental care are not directly comparable with each other. Estimates can be interpreted in the following way. Take parental care for instance. The estimate of $\delta_{parent}(h_0 > \bar{h_0})$ being around 0.41 implies, conditional on time inputs being fixed, if parental care quality increases by 0.01 standard deviation child's skill at age five increases by $0.41 \times \frac{\tau_m+\tau_f}{T_c}$ percent. Where $\frac{\tau_m+\tau_f}{T_c}$ represents the fraction of parental care hours among total care hours needed by the child.

Table 11: Parameters estimated or calibrated outside of the model

Description	Parameter	Estimates	SE
Subsidy Parameters			
Calibrated from Griffen [2019]			
Offer probability index intercept	γ_0^s	-0.86	
Rate ceiling	rc	5.27 *	
Calibrated from Schulman [2019]			
Copay percent	ψ	7.2%	
Income cutoff	$\bar{y}^s$	188% federal poverty level **	
Probability function for availability of relative care (NSECE)			

[26] It is calculated as $\frac{1}{1+\exp(-\gamma_0^{hs})}$.

constant	δ_{r0}	0.369	(0.108)
$\mathbf{I}$(some college)	$\delta_r^{edu=some\ college}$	-0.214	(0.098)
$\mathbf{I}$(bachelor plus)	$\delta_r^{edu=bachelor\ plus}$	-0.708	(0.099)
$\mathbf{I}$(black)	$\delta_r^{race=black}$	-0.229	(0.118)
$\mathbf{I}$(other race)	$\delta_r^{race=other}$	-0.283	(0.096)
$\mathbf{I}$(spouse)	$\delta_r^{withspouse}$	0.270	(0.106)
Parental quality distribution (ECLS-B)			
constant	γ_{parent}	-0.206	(0.016)
$\mathbf{I}$(some college)	$\gamma_{parent}^{edu=some\ college}$	0.300	(0.020)
$\mathbf{I}$(bachelor plus)	$\gamma_{parent}^{edu=bachelor\ plus}$	0.498	(0.019)
$\mathbf{I}$(black)	$\gamma_{parent}^{race=black}$	-0.280	(0.022)
$\mathbf{I}$(other race)	$\gamma_{parent}^{race=other}$	-0.271	(0.019)
standard deviation	σ_{parent}^q	0.972	
Wage Function for Female Worker (NLSY97)			
constant	β_{w0}	1.476	(0.185)
ns^{work} *** (no college)	$\alpha_w^{edu=no\ college}$	0.223	(0.081)
ns^{work} (some college)	$\alpha_w^{edu=some\ college}$	0.208	(0.075)
ns^{work} (bachelor plus)	$\alpha_w^{edu=bachelor\ plus}$	0.159	(0.072)
age	β_{w1}	0.066	(0.015)
age^2	β_{w2}	-0.124	(0.028)
$\mathbf{I}$(full-time)	$\beta_w^{full-time}$	0.054	(0.005)
$\mathbf{I}$(overtime)	$\beta_w^{overtime}$	-0.040	(0.008)
$\mathbf{I}$(some college)	$\beta_w^{edu=some\ college}$	0.006	(0.007)
$\mathbf{I}$(bachelor plus)	$\beta_w^{edu=bachelor\ plus}$	0.091	(0.013)
year==2019	$year_{2019}$	0.703	(0.104)
Wage Shock ϵ_{ijt} Function for Female Worker (NLSY97)			
constant		-0.282	(0.097)
age	β_{w1}	-0.003	(0.008)
age^2	β_{w2}	0.057	(0.014)
$\mathbf{I}$(full-time)	$\beta_w^{full-time}$	0.158	(0.004)
$\mathbf{I}$(overtime)	$\beta_w^{overtime}$	0.083	(0.007)
$\mathbf{I}$(some college)	$\beta_w^{edu=some\ college}$	0.123	(0.005)
$\mathbf{I}$(bachelor plus)		0.296	(0.005)
year==2019	$year_{2019}$	-0.607	(0.038)
rmse		0.373	
Wage Function for Male Worker (NLSY97)			
constant	β_{w0}	2.004	(0.179)
ns^{work} (no college)	$\alpha_w^{edu=no\ college}$	0.073	(0.081)
ns^{work} (some college)	$\alpha_w^{edu=some\ college}$	0.054	(0.073)
ns^{work} (bachelor plus)	$\alpha_w^{edu=bachelor\ plus}$	0.038	(0.071)
age	β_{w1}	0.028	(0.015)
age^2	β_{w2}	-0.040	(0.026)
$\mathbf{I}$(full-time)	$\beta_w^{full-time}$	0.028	(0.007)
$\mathbf{I}$(overtime)	$\beta_w^{overtime}$	-0.030	(0.006)
$\mathbf{I}$(some college)	$\beta_w^{edu=some\ college}$	-0.001	(0.008)

I(bachelor plus)	$\beta_w^{edu=bachelor\ plus}$	0.068	(0.016)
year==2019	$year_{2019}$	0.597	(0.111)
Wage Shock ϵ_{ijt} Function for Male Worker (NLSY97)			
constant		-0.843	(0.102)
age	β_{w1}	0.046	(0.008)
age^2	β_{w2}	-0.046	(0.015)
I(full-time)	$\beta_w^{full-time}$	0.230	(0.005)
I(overtime)	$\beta_w^{overtime}$	0.069	(0.006)
I(some college)	$\beta_w^{edu=some\ college}$	0.112	(0.005)
I(bachelor plus)	$\beta_w^{edu=bachelor\ plus}$	0.246	(0.006)
year==2019	$year_{2019}$	-0.451	(0.041)
rmse	σ_ϵ	0.382	

* Rate ceiling has been adjusted to be in 2019 dollars.

** Parameters are calibrated based on average state-level policy rules weighted by state population.

*** ns^{work} represents the fraction of nonstandard working hours among total working hours.

Table 12: SMM estimates inside the model

Description	Parameter	Estimates	SE
Quality distribution			
Relative care			
constant	γ_{r0}	-1.111	(0.026)
I(some college)	$\gamma_r^{edu=some\ college}$	0.692	(0.018)
I(bachelor plus)	$\gamma_r^{edu=bachelor\ plus}$	1.289	(0.032)
I(black)	$\gamma_r^{race=black}$	-0.131	(0.001)
I(other race)	$\gamma_r^{race=other}$	0.700	(0.016)
standard deviation	σ_r^q	0.361	(0.018)
Provider(standard hours only)			
constant	γ_{ps0}	-0.801	(0.022)
I(some college)	$\gamma_{ps}^{edu=some\ college}$	0.389	(0.019)
I(bachelor plus)	$\gamma_{ps}^{edu=bachelor\ plus}$	0.954	(0.016)
I(black)	$\gamma_{ps}^{race=black}$	-0.422	(0.014)
I(other race)	$\gamma_{ps}^{race=other}$	-0.075	(0.001)
I(Head Start)	γ_{hs}	0.326	(0.014)
standard deviation	σ_{ps}^q	0.347	(0.046)
Provider(also nonstandard hours)			
constant	γ_{pa0}	-2.112	(0.027)
I(some college)	$\gamma_{pa}^{edu=some\ college}$	0.715	(0.055)
I(bachelor plus)	$\gamma_{pa}^{edu=bachelor\ plus}$	0.962	(0.026)
I(black)	$\gamma_{pa}^{race=black}$	-0.161	(0.006)
I(other race)	$\gamma_{pa}^{race=other}$	-0.211	(0.008)
standard deviation	σ_{pa}^q	1.283	(0.019)
correlation of provider quality $corr(ps, pa)$	ρ_{pq}	0.035	(0.002)

Probability function for free relative care			
constant	δ_{r0}^{free}	1.610	(0.033)
$\mathbf{I}$(some college)	$\delta_{r}^{free,\ edu=some\ college}$	-0.807	(0.039)
$\mathbf{I}$(bachelor plus)	$\delta_{r}^{free,\ edu=bachelor\ plus}$	-0.009	(0.002)
$\mathbf{I}$(black)	$\delta_{r}^{free,\ race=black}$	-0.164	(0.008)
$\mathbf{I}$(other race)	$\delta_{r}^{free,\ race=other}$	-0.010	(0.002)
Probability of relative care accessible during nonstandard hours			
probability	Pr_r^{nstd}	0.528	(0.002)
Price function			
Relative care			
constant	β_{r0}	1.155	(0.024)
quality	β_{r1}	0.054	(0.002)
standard deviation	σ_r^p	0.017	(0.007)
Provider(standard hours only)			
constant	β_{ps0}	1.665	(0.031)
quality	β_{ps1}	0.059	(0.003)
standard deviation	σ_{ps}^p	0.339	(0.007)
Provider(also nonstandard hours)			
constant	β_{pa0}	1.600	(0.033)
quality	β_{pa1}	0.145	(0.005)
standard deviation	σ_{pa}^p	0.362	(0.007)
correlation of provider price $corr(ps, pa)$	ρ_{pp}	0.345	(0.008)
Skill production function			
constant	δ_0	-0.274	(0.007)
initial skill	δ_1	0.334	(0.005)
parental care productivity ($h_0 \leq \bar{h_0}$)	$\delta_{parent}(h_0 \leq \bar{h_0})$	0.004	(0.006)
parental care productivity ($h_0 > \bar{h_0}$)	$\delta_{parent}(h_0 > \bar{h_0})$	0.414	(0.023)
relative care productivity ($h_0 \leq \bar{h_0}$)	$\delta_r(h_0 \leq \bar{h_0})$	3.452	(0.350)
relative care productivity ($h_0 > \bar{h_0}$)	$\delta_r(h_0 > \bar{h_0})$	0.081	(0.006)
provider care productivity ($h_0 \leq \bar{h_0}$)	$\delta_p(h_0 \leq \bar{h_0})$	2.795	(0.139)
provider care productivity ($h_0 > \bar{h_0}$)	$\delta_p(h_0 > \bar{h_0})$	0.115	(0.008)
standard deviation	σ_h	0.770	(0.003)
Utility function			
Mother's leisure	γ_{lm}	0.125	(0.019)
Father's leisure	γ_{lf}	2.289	(0.150)
Child skill at the end of the period	γ_{h1}	11.893	(4.290)
Parental care hours	γ_{parent}	1.719	(0.064)
Head Start Probability			
constant in logit func	γ_0^{hs}	0.663	(0.113)
$\mathbf{I}$(inc above poverty)	γ_1^{hs}	-3.717	(0.658)

Source1: National Survey of Early Care and Education (NSECE) 2019.

Source2: National Longitudinal Survey of Youth 1997 (NLSY97).

Source3: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B). All statistics use sampling weights provided by the ECLS-B.

6.2 Model Fit

Figure 1: Model Fit

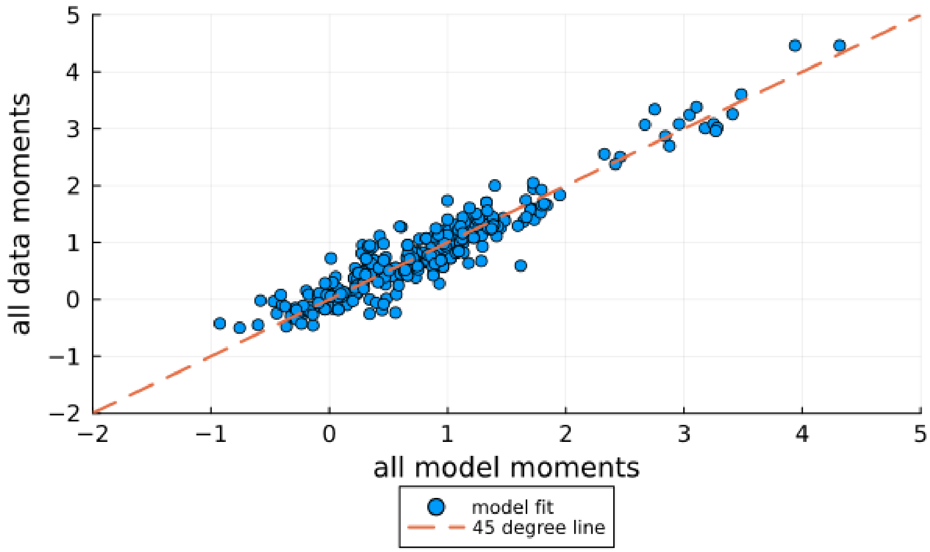


Figure 1 shows the fit of the model moments with the data moments weighted by inverse standard deviation. Table 13 compares part of the model moments, regarding childcare usage and maternal labor force participation, with the data moments. The model reasonably fits those moments and the socioeconomic status-related trends. The supporting parameter identification figures are presented in Appendix F.2.

To ensure the reliability of the policy environment simulated in the model, I compare the Head Start and subsidy policy environments in the model with those in real-world settings. In 2019, there were around 19.57 million children in the US aged under five, and around 0.87 million, around 4.45%, of them were enrolled in the HS programs.[27] The term Head Start in this paper refers to the Head Start program as a whole, including Head Start, Early Head Start, and other associated programs. In my model simulation, around 4.3% of the households are enrolled in the Head Start program. Based on the reports from the Department of Health and Human Services Chien [2022], under federal rules, in 2019, 24% of the children ages between 0 and 12 are potentially eligible for childcare subsidies. Among those who are potentially eligible for the subsidy, around 16%[28] actually received subsidies. In my model simulation, for the group of households with young child age below five, around

[27]Head Start Program Facts: Fiscal Year 2019. https://eclkc.ohs.acf.hhs.gov/about-us/article/head-start-program-facts-fiscal-year-2019

[28]It is calculated as 2 million out of 12.5 million children.

17.3% of households meet the subsidy eligibility requirement. And among those who are eligible for childcare subsidies, around 13.1% actually receives the subsidies.

Table 13: Comparison of data and model moments

	Data			Model		
	no college	some college	Bachelor+	no college	some college	Bachelor+
Maternal Labor Supply (NSECE)*						
% of mother working	0.35	0.53	0.63	0.46	0.56	0.67
total hours	11.69	18.04	21.75	14.55	18.78	24.55
fraction of nonstandard hour among total hours	0.30	0.24	0.16	0.33	0.32	0.22
Child Care Arrangements (NSECE)*						
parental care						
total hours	76.46	70.37	66.97	74.00	67.56	58.21
fraction of nonstandard hour among total hours	0.49	0.55	0.60	0.51	0.54	0.65
provider care						
% of hh using provider care	0.24	0.34	0.56	0.24	0.34	0.46
total hours	7.09	11.18	17.03	9.84	14.26	22.13
fraction of nonstandard hour among total hours	0.20	0.14	0.11	0.21	0.24	0.15
relative care						
% of hh using relative care	0.21	0.29	0.23	0.14	0.17	0.18
total hours	6.63	8.68	6.12	6.16	8.18	9.65
fraction of nonstandard hour among total hours	0.37	0.32	0.22	0.38	0.34	0.30
Skill Development (ECLS-B)**						
skill at the end of the period	-0.34	-0.03	0.38	-0.29	-0.05	0.24

* *Source:* The National Survey of Early Care and Education (NSECE) 2019 data.

** *Source:* US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B). *Notes:* All statistics use sampling weights provided by the ECLS-B.

7 Counterfactual Simulations

After estimating the model, I simulate three groups of counterfactual scenarios, with specific attention paid to the relatively more vulnerable lower SES households, whose mothers do not have college education. The first group of counterfactual scenarios tries to understand lower SES mothers' demand for care and work during nonstandard hours and examines which schedule-related factors hinder lower SES mothers from participating in the labor force and from utilizing formal childcare providers. The second group analyzes how existing Head Start and Subsidy policies could expand to further support these disadvantaged households in improving their well-being and the potential scale of these policy impacts. The final set of simulations investigates the impact of implementing other policies, such as lump-sum subsidies or direct schedule-related subsidies, assessing the magnitude of their effects.

7.1 Wage Premium v.s. Care Options During Nonstandard Hours

Several schedule-related counterfactual situations are simulated and are presented in Table 14 to understand why lower SES workers work a higher amount of nonstandard hours and what schedule factors influence their labor participation and provider care usage the most. These counterfactual scenarios include the situation where female workers have no wage premium for the nonstandard schedule $\alpha_w^{edu} = 0$, results of which are presented in column (1); the situation where average provider prices are the same in nonstandard hours than in standard hours $\vec{\beta}_{pa} = \vec{\beta}_{ps}$, results of which are presented in column (2); and the situation where average provider quality is the same in nonstandard hours than in standard hours $\vec{\gamma}_{pa} = \vec{\gamma}_{ps}$, results of which are presented in column (3).[29]

Table 14: Schedule related counterfactual situations

	Baseline	(%) **percentage change** under different counterfactual situations		
	Mother with no college education	No wage premium for nonstandard hours * (1)	Price structure are the same btw ps and pa (2)	Average quality are the same btw ps and pa (3)
Maternal Work Arrangement				
$\mathbf{I}$(work)	0.46	-3.25	0.00	20.35
total work hours	14.55	-1.99	0.00	28.67
frac of nonstandard hrs	0.33	-75.19	-0.54	26.90
Care Arrangement				
$\mathbf{I}$(use provider care)	0.24	-1.79	0.00	61.17
total provider hours	9.84	-0.06	-0.39	102.29
frac of nonstandard hrs	0.21	-31.56	-2.90	82.02
Skill Development				
$\ln h_1$	-0.29	$\downarrow$ 0.11	$\downarrow$ 0.02	$\uparrow$ 84.24
(\$/week) hh inc bef subsidy	1148.62	1126.08	1148.54	1230.72 (+82)
provider cost bef subsidy	46.58	46.87	47.30	105.68 (+59)
provider cost after subsidy	36.18	35.80	37.13	93.27 (+57)

* Since paternal labor is not a choice in the model, this simulation keeps the wage premium for paternal labor constant, sets the maternal labor premium for nonstandard hours as zero, and simulates the impacts.

As is expected, Table 14 shows that when there is no wage premium during nonstandard hours, female workers are 3.3% less likely to participate in the labor market and are much less likely to work in a nonstandard schedule. The fraction of nonstandard working hours among total working hours decreases by around 75.2%. This also leads to a decrease in provider care demand during nonstandard hours. Provider care demand decreases by around 1.8%, and the fraction of nonstandard care hours among total care hours decreases by around 31.6%. Though it is estimated that price is more sensitive to quality for providers who

[29] $\vec{\beta}_{pa} = \{\beta_{pa0}, \beta_{pa1}\}$, and $\vec{\gamma}_{pa} = \{\gamma_{pa0}, \gamma_{pa1}^{edu}, \gamma_{pa1}^{race}\}$.

operate during any schedule than providers who only operate during standard schedule, differences in price structures in standard hours versus nonstandard hours have mild effects on influencing household behavior.

Quality differences between those two types of providers and among standard and nonstandard schedules have a vital influence in determining household choices. When the average quality of care during nonstandard hours is the same as the average quality of care during standard hours, mothers are 20.4% more likely to work, and their working hours increase by around 28.7%; additionally, households are 61.2% more likely to use provider care and the care hours almost double compared with the care hours under the baseline. Due to these work and care arrangement changes, the child's skill at age five, on average, increases by 84.2%. Table 14 also shows that the adjusted choices increase household income by 82 dollars per week, and provider cost after subsidy increases by 57 dollars per week. The net gain for households on average is around 25 dollars per week, and the additional cost to the government is about 2 dollars per week. This indicates that when high-quality care options are available among nonstandard schedules, without any additional government intervention, households self-adjust toward an improved situation with increased maternal labor participation, greater enrollment in formal care, enhanced child skills, and improved household income.

Figure 2 focuses on the base group of households (mothers without college education, white) and provides a more intuitive illustration of the labor participation and care usage trends when the average quality of all-schedule providers is gradually improved toward the quality of standard-hour-only providers. The schedule trends explicitly show that the care schedule is relatively more sensitive to quality change than the work schedule.

Table 15 shows more information about how the labor force participation gap and the formal care enrollment gap between lower SES households (mothers without college education) and higher SES households (mothers with bachelor's degrees or higher) are affected by these different counterfactual scenarios. Counterfactual simulations are only implemented among lower SES households. If quality faced by lower SES households during the nonstandard schedule is improved, as has been simulated in column (3), this closes around 45% of the maternal labor force participation gap and around 67% of the formal care enrollment gap.

7.2 Head Start and Childcare Subsidies

In this section, I relax the policy rules of the existing Head Start and Subsidies policies and assess the counterfactual policy impacts on lower SES households. The counterfactual scenarios aim to either increase the quality of care during nonstandard hours, reduce care

Figure 2: For base households, how maternal labor participation and provider care usage change with the average quality of providers who are accessible during any schedule.

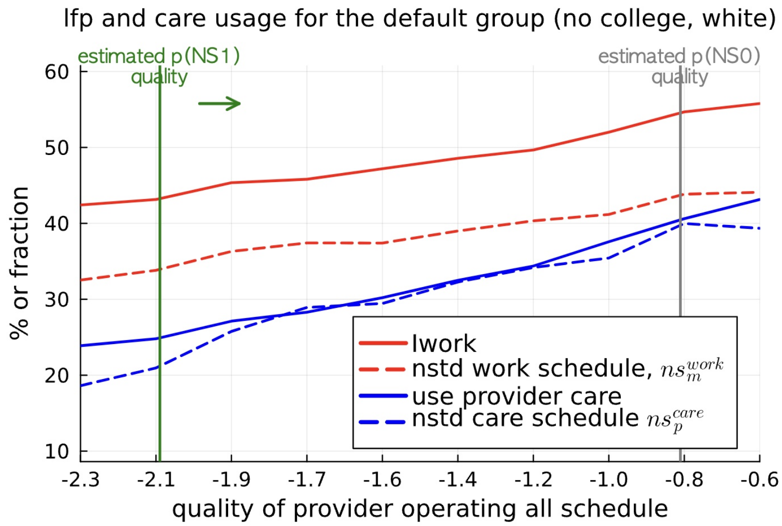


Table 15: How this closes the gap between lower SES and higher SES households

	Baseline			**Gap close by what (%) percentage** under different counterfactual situations		
	Mother with no college education	Mother with bachelor + degree	Gap between no collge v.s. bachelor +	No wage premium for nonstandard hours (1)	Price structure are the same btw ps and pa (2)	Average quality are the same btw ps and pa (3)
Maternal Work Arrangement						
I(work)	0.46	0.67	0.21	7.18	0.00	-44.98
total work hours	14.55	24.55	10.00	2.89	0.00	-41.72
Care Arrangement						
I(use provider care)	0.24	0.46	0.22	1.95	0.00	-66.57
total provider hours	9.84	22.13	12.29	0.05	0.31	-81.85
Skill Development						
$\ln h_1$	-0.29	0.24	0.53	0.06	0.01	-45.66

costs, or achieve both for more vulnerable households.

In the baseline model, Head Start programs provide 20 hours per week (or 1,020 hours per year) of free higher-quality care to households who have access to the program. It is assumed to be available in providers who only operate in standard hours. Eligible households whose before subsidy household income is below 100% of the poverty level are estimated to have access to the program with probability $\pi_{hs} = 0.66$; and households whose before subsidy household income is between 100%-130% of the poverty level are estimated to have access to the program with a much lower probability $\pi_{hs} = 0.045$. Table 17 presents the policy impacts when I gradually relax the policy rules of the Head Start program for lower SES households. In column (1), I relax the limitation on hours and allow the program to be available for up to fifty hours during the standard schedule, $\bar{h}^{hs} = 50$ hours.[30] In column (2), additional relaxation is implemented, and the Head Start program is available to all types of providers, contrary to the baseline model where the Head Start program is only available to providers offering only standard hours. Under this counterfactual scenario, providers who operate during any schedule could also be the grantee of the Head Start program with quality being $\gamma_{hs} = 0.326$ standard deviation higher than the average quality of providers with the same type. In column (1) and column (2), the Head Start program is rationed, and not all eligible households have access to the program, i.e. $\pi_{hs} < 1$. In the counterfactual simulation in column (3), I further expand the program to be accessible to all households who meet the eligibility requirements. This is to say that those whose household income is below 130% of the poverty level are guaranteed to have access to the Head Start program, $\pi_{hs} = 1$.

Table 17 shows that notable impacts on lower SES households emerge when the Head Start program is available during the nonstandard schedule and is additionally accessible to all eligible households. In the counterfactual scenario of column (2), during nonstandard hours, some households also have access to free and relatively higher-quality provider care. Compared with the baseline, provider care usage increases by 1.7%, and care hours increase by around 4.2%; child skill, on average, increases by around 2.2%; while there is no significant impact on maternal labor force participation. When further expanding the accessibility of the program, provider care usage increases by 20.5%, and care hours increase by around 16.3%. By utilizing the provider care, mothers are 5% more likely to participate in the labor force and work 2.4% more hours. These arrangement changes lead child skills to increase by 24%. Compared with the baseline model, for this group of households whose mothers do not have college education, the government's subsidy cost, on average, increases by about 18 dollars per week per household. Table 17 provides additional insights into how the gap between lower SES households and higher SES households is closed under each scenario. If

[30] Fifty hours are calculated as hours from 8 a.m. to 6 p.m., Monday through Friday.

lower SES households who are eligible for Head Start are guaranteed to have full access to Head Start during any schedule, this closes the maternal labor participation gap by 10.9%, the formal care enrollment gap by 22.3%, and the child skill gap by 13.0%.

Table 16: Policy impacts when gradually expanding Head Start Program

	Baseline	**(%) percentage change** under different counterfactual situations		
	Mother with no college education	No limitation on hrs during standard schedule (1)	+ Accessible in pa * $\gamma_{hs} = 0.326$ (2)	+ Accessible to all eligible hh $\pi_{hs} = 1$ ** (3)
Maternal Work Arrangement				
$\mathbf{I}$(work)	0.46	-0.10	-0.01	4.94
total work hours	14.55	-0.31	-0.91	2.38
frac of nonstandard hrs	0.33	-0.07	3.64	-1.79
Care Arrangement				
$\mathbf{I}$(use provider care)	0.24	0.20	1.72	20.47
total provider hours	9.84	2.58	4.16	16.31
frac of nonstandard hrs	0.21	-0.41	8.53	9.84
Skill Development				
$\ln h_1$	-0.29	↑ 0.32	↑ 2.21	↑ 23.98
($/week) hh inc bef subsidy	1148.62	1147.60	1145.64	1146.70 (-1.92)
provider cost bef subsidy	46.58	48.07	48.94	57.05 (+10.47)
provider cost after subsidy	36.18	33.47	31.93	27.86 (-8.32)

* pa is the type of provider who operates during any schedule, both standard and nonstandard schedules.

** In the baseline model, π_{hs} is around 0.66 for households whose income is below 100% of the poverty level and is around 0.045 for households whose income is between 100% to 130% of the poverty level.

Table 18 presents the impacts of relaxing the current subsidy policy rules. In the baseline model, the rate ceiling is $5.25/hour ($rc = 5.25\$$), which is around the 75th quantile of the market price. Conditional on using the subsidy, out-of-pocket copayment is 7.2% of household income, $\psi = 7.2\%$. For households who are eligible for the subsidy, around 30% of them are rationed to have access to the program, $\pi_s = 0.3$. In column (1), I simulate a situation in which the rate ceiling, rc, equals the maximum market price; thus, the out-of-pocket marginal rate remains zero. In column (2), I simulate a situation in which there is no copayment $\psi = 0$. In column (3), the subsidy is no longer rationed, and all eligible household have access to the subsidy, $\pi_s = 1$. Overall, these policy changes do not have large impacts on choices by lower SES households.[31] It should be noted that in these counterfactual scenarios,

[31] These policy changes also do not significantly impact closing the associated gaps, especially the child skill gap, between lower SES households and higher SES households. Results are presented in Appendix G Table 26.

Table 17: How this closes the gap between lower SES and higher SES households

	Baseline			Gap close by what (%) percentage under different counterfactual situations		
	Mother with no college education	Mother with bachelor + degree	Gap between no collge v.s. bachelor +	No limitation on hrs during standard schedule (1)	+ Accessible in pa $\gamma_{hs} = 0.326$ (2)	+ Accessible to all eligible hh $\pi_{hs} = 1$ (3)
Maternal Work Arrangement						
I(work)	0.46	0.67	0.21	0.22	0.01	-10.92
total work hours	14.55	24.55	10.00	0.45	1.33	-3.47
Care Arrangement						
I(use provider care)	0.24	0.46	0.22	-0.21	-1.87	-22.27
total provider hours	9.84	22.13	12.29	-2.07	-3.33	-13.05
Skill Development						
$\ln h_1$	-0.29	0.24	0.53	-0.18	-1.20	-13.00

the analyses presented reflect the potential policy influence on lower SES households. This is not directly comparable to the estimated intent to treat or the treatment on the treated effects of subsidies, as documented in existing literature. Since in the baseline model, only around 9% of the households have access to the subsidy, and 4% of the households take up and receive the subsidy, the policy's impacts on lower SES households are expected to be small.

Table 18: Subsidies related counterfactual situations

	Baseline	(%) percentage change under different counterfactual situations		
	Mother with no college education	No rate ceiling rc (1)	No copayment $\psi = 0$ (2)	Accessible to all eligible hh $\pi_s = 1$ * (3)
Maternal Work Arrangement				
I(work)	0.46	0.11	0.11	0.36
total work hours	14.55	0.07	-0.21	2.94
frac of nonstandard hrs	0.33	-0.33	0.42	-3.91
Care Arrangement				
I(use provider care)	0.24	0.26	1.06	3.66
total provider hours	9.84	0.17	0.02	-4.58
frac of nonstandard hrs	0.21	-1.02	2.25	16.79
Skill Development				
$\ln h_1$	-0.29	0.00	$\downarrow$ 0.01	$\downarrow$ 3.42
($/week) hh inc bef subsidy	1148.62	1148.69	1147.91	1147.93 (-0.7)
provider cost bef subsidy	46.58	46.71	46.53	46.55 (-0.0)
provider cost after subsidy	36.18	35.75	33.47	31.27 (-4.9)

* In the baseline model, π_s is 0.3 for households whose income is below 188% of the poverty level.

7.3 Other Types of Subsidies

In addition to the existing policies discussed in this paper, another series of counterfactual policy simulations is implemented, and candidate policies include unitary price subsidies and lump-sum subsidies.

For unitary price subsidy, the following counterfactual scenarios are simulated: (1) subsidize any provider care used during standard hours with the mean hourly price; (2) subsidize any provider care used during nonstandard hours with the mean hourly price; (3) subsidize the standard hours for households whose household income is below the poverty line; (4) subsidize the nonstandard hours for households whose household income is below the poverty line. In these unitary price subsidy counterfactual situations, subsidies are capped at the price charged. Detailed results are shown in Appendix G Table 27. When there is no household income restriction under a direct price subsidy, this can incentivize households to be 8.7% more likely to use provider care if the price subsidy is imposed on standard hours and 5.1% more likely to use provider care if the price subsidy is imposed on nonstandard hours. The changes in work and care schedules are driven directly by the subsidies imposed on different schedules. For example, when subsidies are allocated to standard hours without any income restrictions, mothers work 7.8% less of the fraction of nonstandard hours among total hours and use 31.7% less of the fraction of nonstandard care hours among total hours. This has a very minimal impact on improving the child's skill at age five, which is improved by only 0.22%. Compared to subsidizing nonstandard care hours, subsidizing standard care hours is better in improving provider care enrollment and usage but slightly worse in improving the labor participation of mothers. When additional restrictions on family income are applied, the size of the impacts becomes negligible.[32]

As for the lump-sum subsidy, the magnitude of which equals the average weekly cost of provider care, I simulate the following counterfactual ways of implementing the policy: (1) assigns lump-sum subsidy to all households; (2) distributes the subsidy only to households whose income is below the poverty level; column (3) additionally imposes labor participation requirement. The lump-sum subsidy does not appear to be a good option for improving labor participation or provider care enrollment, no matter what constraints are added. Additionally, the results from the first counterfactual analysis implicitly reveal that switching from using provider care to using other types of care is not necessarily harmful to a child's skill development.[33]

[32]These policy changes again do not have much impact on closing the associated gaps between lower SES households and higher SES households. Results are presented in Appendix G Table 28.

[33]Detailed results are presented in Appendix G Table 29.

8 Conclusion

Schedule compensation is a common practice in the labor market, and workers from the lower SES households value the differentials more and self-select to work more during nonstandard hours compared with their higher SES counterparts. During nonstandard hours, care options are limited, and high-quality providers, like center-based providers, are much less likely to be available. This paper focuses on the trade-off between the schedule wage premium versus constrained access to high-quality care, which is mainly faced by lower SES households with young children. The model in this paper and the counterfactual analyses evaluate whether the lack of available high-quality childcare in the nonstandard schedule impedes maternal labor market outcomes, formal care usage, and child development. Additionally, I investigate what policies could potentially be implemented to help the lower SES households out of the dilemma.

I approach this question by estimating a model in which households make joint determinations of maternal labor supply and childcare usage during various schedules. In the model, there are parental care and multiple types of non-parental care options (relative, provider operating during the standard schedule, and provider operating during any schedule) with heterogeneous quality and price distributions, as well as operating times. Wage differentials are paid to those working nonstandard schedules, and workers have higher hourly wages if they work a larger fraction of nonstandard hours among total working hours.

Through the wage analysis using the NLSY97 data, I find that schedule compensation is relatively larger for workers with lower educational attainment compared with workers with higher educational attainment. For the no college education workers, if the worker changes from fully working in a standard schedule toward fully working in a nonstandard schedule, on average, the worker's wage increases by around 14.3%; and for workers with bachelor or above bachelor degree, such schedule change increases the worker's wage by around 10.0%. Heterogeneity analysis also reveals that the schedule wage premiums are larger for female workers than for male workers.

The counterfactual simulations, using the estimated model, show that the lower SES households' labor supplies in nonstandard schedules are mostly driven by the schedule premium, and these work schedule choices further lead to the demand for care during nonstandard hours. It also demonstrates that differences in price structures during standard and nonstandard hours have negligible power in explaining the schedule choices, while differences in quality structures are important for understanding household labor participation and care arrangement decisions. The lack of available high-quality providers among nonstandard schedules impedes mothers from working and impedes children's enrollment in provider care. Improving the average quality of any-schedule providers to match the average quality of standard-hour-only providers causes maternal labor participation to increase by around 20.4%, and provider care enrollment to increase by around 61.2%. As a result, the child skill gap between lower SES and higher SES households shrinks by 45.7%.

I also implement counterfactual policy simulations. The policy that makes higher-quality childcare more available during nonstandard schedules is estimated to have the largest impact on the well-being of lower SES households. When the Head Start program, a higher-quality childcare program, is available during nonstandard hours and is accessible to all eligible lower SES households, mothers in this group are 4.9% more likely to participate in the labor force, 20.5% more likely to enroll their children in formal provider care, and their children's skills improve by around 24.0%. However, these counterfactual simulations are not directly comparable with each other without considering the government budget constraints or the difficulties of implementation.

In summary, lower SES households select into working more nonstandard schedules due to the schedule wage premium, and the low quality of the provider care during these schedules limits their labor participation and provider care enrollment. Provider quality among nonstandard hours is vital for explaining maternal labor outcomes, childcare usage, and child's skill development. Having high-quality provider care, like Head Start, accessible during nontraditional schedules eases the trade-offs faced by lower-SES households and should be considered in future policy design.

Appendices

A Motivating Facts

A.1 Workers from Lower SES households are more likely to Work Nonstandard Hours

Table 19: Percentage of Worker who Works and Works Nontraditional Schedule in ATUS

	all		**without young child**		**with young child**	
	(%) employed	(%) workers work nontraditional hours (cond. on employed)	(%) employed	(%) workers work nontraditional hours (cond. on employed)	(%) employed	(%) workers work nontraditional hours (cond. on employed)
Female						
No college	55.25	45.78	59.58	43.83	39.89	56.44
Some college	68.36	33.48	71.64	33.52	53.61	33.28
Bachelor plus	84.70	11.88	86.70	13.75	78.22	4.99
Male						
No college	71.20	46.21	70.06	47.44	77.13	40.28
Some college	75.58	43.65	74.34	44.03	83.47	41.69
Bachelor plus	87.21	18.29	86.79	19.67	88.44	14.06
All workers						
No college	64.05	46.05	65.55	46.06	57.55	46.00
Some college	71.71	38.47	72.93	38.67	65.34	37.42
Bachelor plus	85.85	14.84	86.74	16.42	83.07	9.49
All	72.87	31.86	74.20	32.77	67.27	27.71

Source: The ATUS 2017-2018 data.
Note: This tabulation is based on the respondent ages between 18-50.
* Employment refers to employment by government and firm, and excludes self-employment.
** Nontraditional schedule indicator equals one if most of the work is done outside of 6 a.m. and 6 p.m. or if usually working on Saturday or Sunday.

A.2 Supply Scarcity During Nontraditional Hours

As is revealed in the Early Childhood Longitudinal Study, Birth Cohort (ECLS-B) data,[34] only around 11.5% of the center-based care provides service during nontraditional hours. The percentage is higher for non-center-based types of care, such as nannies and home-based care. Around 28.6% of the non-center-based providers provide service during nontraditional hours. Compared with formal care providers, informal relative care is shown to be with more flexibility and around 68% of them take care of the child during nontraditional hours.

A.2.1 The ECLS-B Data

A.2.2 The NSECE 2019 Data – Provider Survey

Center-Based Care

[34] *Source*: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Table 20: Operation Schedule by Provider's Type

Percent of providers (%)	provider center-based	provider non-center-based	relative care	Total
operate only traditional hours	88.49	71.45	32.05	62.23
provide service during nontraditional hours	11.51	28.55	67.95	37.77

Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Notes: Sample sizes are rounded to the nearest 50. All statistics use sampling weights provided by the ECLS-B.

* Whether operating in nontraditional hours is only asked in wave 2.

Table 21: Percentage of center-based providers who operate in nonstandard hours

Variable		based on providing service to				
(%) **center-based provider operates**	all	infant	1 yr	2 yr	3 yr	4yr
in evening	2.44	4.05	3.8	3.28	2.53	2.36
overnight	6.66	8.65	7.97	7.94	6.95	6.48
on weekends	3.23	4.69	4	3.55	2.97	2.92
any nonstandard hours	9.93	13.3	11.9	11.5	9.95	9.47

		based on providing service to				
(%) **center-based seats provided**	all	infant	1 yr	2 yr	3 yr	4yr
in evening	2.69	4.37	4.18	3.42	2.31	2.03
overnight	5.49	7.48	7.31	7.42	5.74	5.08
on weekends	3.29	6.06	4.76	3.56	2.71	2.56
any nonstandard hours	9.05	13	11.5	10.6	8.04	7.4

Source: NSECE 2019 Center-Based Provider data. Data has been weighted.

Home-Based Listed Provider

The NSECE 2019 home-based data only provides categorized total hours of care provided in the past week and hours provided on each weekday. Without detailed schedule information of opening and close times of the care provider, the best that I can do is to create rough indicators on whether the program operates during nonstandard hours, on weekends, or any nonstandard schedule. For comparison purposes, I define the variable based on similar rules used in the NSECE 2019 center-based survey data, in which evening is defined as from 7 p.m. to 11 p.m. and night is defined as from 11 p.m. to 6 a.m. Using the home-based data, I define the home-based provider who provides service during nonstandard hours on weekdays if the provider works more than 13 hours (the interval between 7 p.m. and 6 a.m. used by center-based survey data) on any weekday in the past week. And define the home-based provider providing service during weekends if the difference between total weekly hours and total weekday hours is greater than zero.

Table 22: Percentage of home-based listed providers who operate in nonstandard hours

	based on providing service to		
(%) home-based listed operates	all	0-3 yr	3-5 yr (not in kindergarten)
week day nonstandard hours	65.90	55.80	67.20
on weekends	48.00	47.90	48.00
any nonstandard hours	72.40	66.70	73.10
	based on providing service to		
(%) home-based listed seats provided	all	0-3 yr	3-5 yr (not in kindergarten)
week day nonstandard hours	69.30	62.00	69.70
on weekends	49.90	47.40	50.00
any nonstandard hours	73.90	66.50	74.20

Source: the NSECE 2019 Home-Based Provider data. Data has been weighted.

Home-Based Unlisted Providers

Table 23: Percentage of home-based unlisted providers who operate in nonstandard hours

	based on providing service to		
(%) home-based unlisted care operates	all	0-3 yr	3-5 yr (not in kindergarten)
week day nonstandard hours	24.70	25.30	24.30
on weekends	46.50	49.60	44.80
any nonstandard hours	54.30	54.70	54.10

	based on providing service to		
(%) home-based unlisted care seats provided	all	0-3 yr	3-5 yr (not in kindergarten)
week day nonstandard hours	27.50	25.20	28.50
on weekends	45.90	48.00	45.10
any nonstandard hours	55.90	53.50	56.80

Source: the NSECE 2019 Center-Based Provider data. Data has been weighted.

Table 24: Schedule and Hourly Price Paid Based on Provider's Type

	providers		households who use the service		
Variable	(%) provide service during nontraditional hours* in the past week	(%) free charge	all prices**	price>0	(%) free charge
Conditional on the Provider Type					
Center-based ECE	9.93	26.89	3.52	4.95	27.90
Listed Home-based	72.40	3.22	5.49	5.51	0.36
Unlisted Home-based	54.30	82.00	0.92	4.26	78.40

Source: The first column is from the NSECE 2019 Center-Based and Home-Based data. The last three columns are from the NSECE 2019 Household Survey data.

* Schedule details are reported in Appendix A.2.

** Prices presented are the hourly prices paid by the household, which are prices after subsidies.

B Motivation: Focusing on Mother's Labor Supply

B.1 Data Pattern: Maternal Labor Supply is More Correlated with Childcare Usage

Figure 3 and Figure 4 show that compared with paternal labor supply, maternal labor supply is more correlated with childcare usage. This is true both considering hours of work and care and considering the proportion of standard work and care hours among total hours. The flat relationship revealed in Figure 3 between the working hours of the father with spouse and non-parental childcare usage persists for different educational groups.

Figure 3: Linear-fit of the relationship between working hours and non-parental caring hours

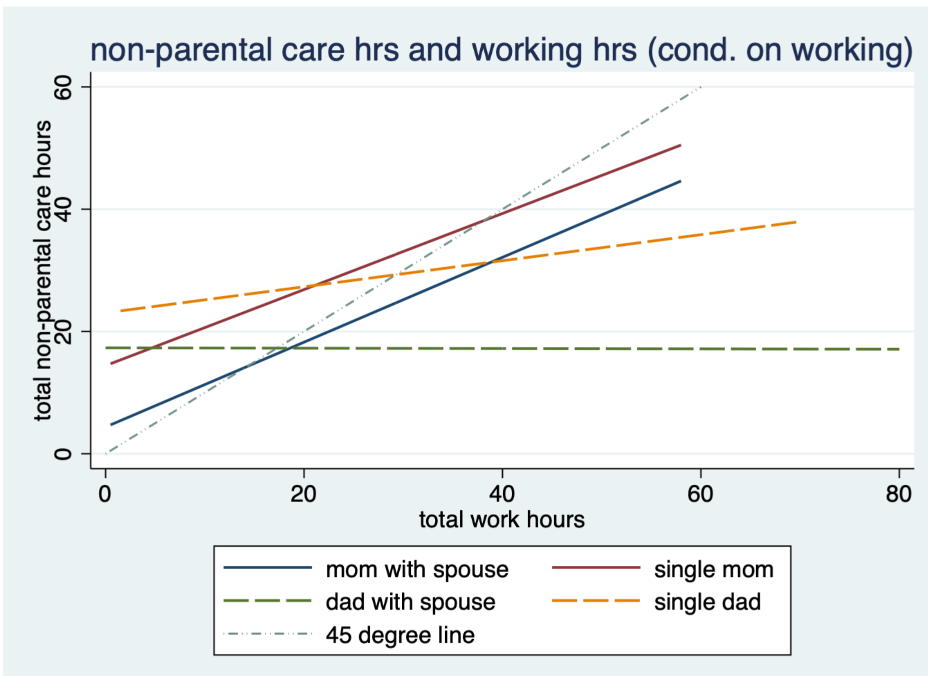
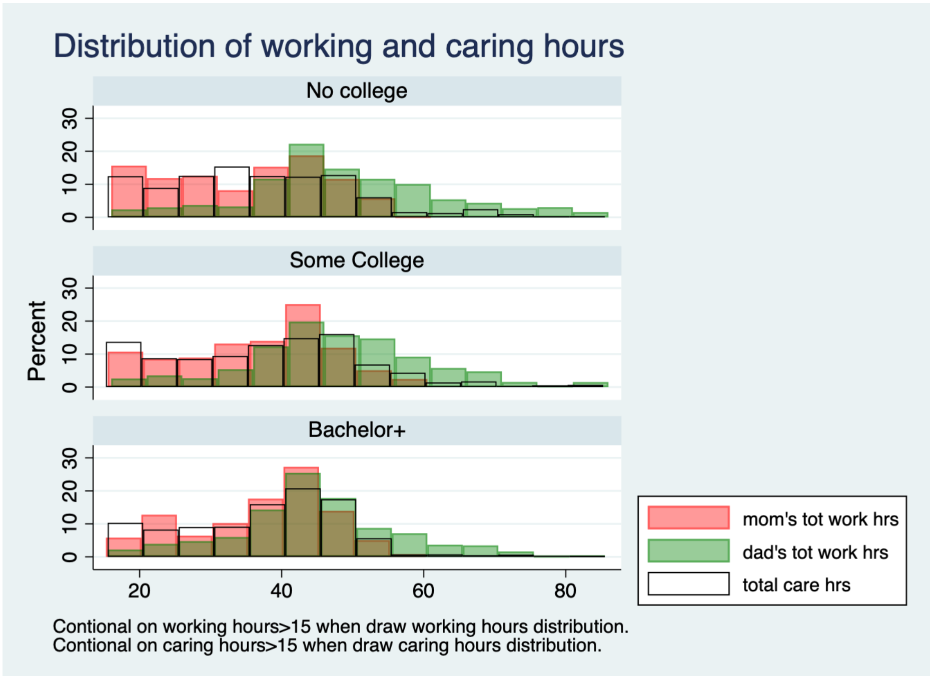
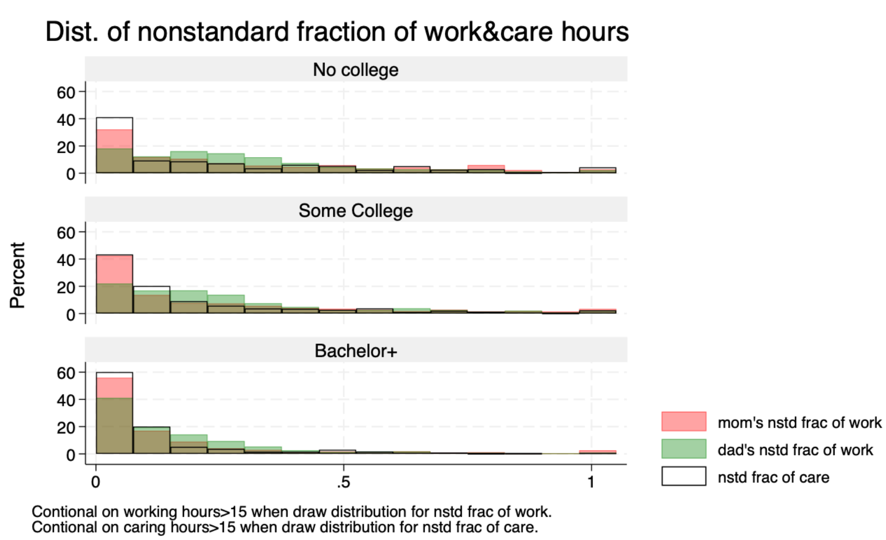


Figure 4: Distribution of work and care, cond. on work(or care) hours > 15h



(a) Distribution of total work or care hours

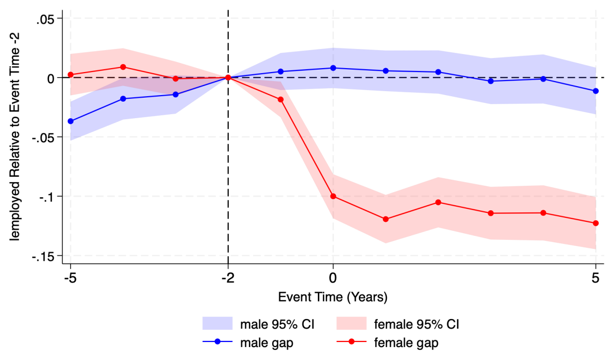


(b) Distribution of fraction of standard hours

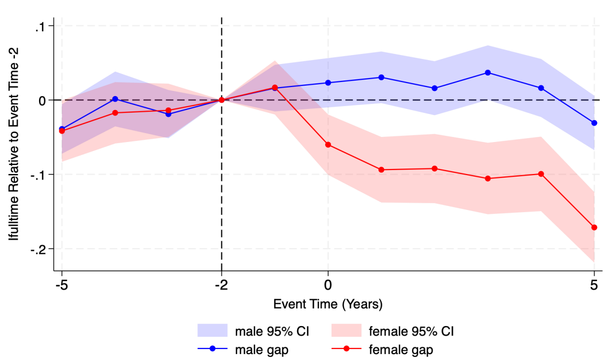
B.2 Event Study

This section aims to provide more concrete evidence on how maternal labor decisions, both labor participation decisions and work schedule choices, are influenced by having a child. This section also reveals that compared with the father, the mother is more likely to be the person who makes adjustments over labor choices when having a child and when facing schedule conflicts between work and care.

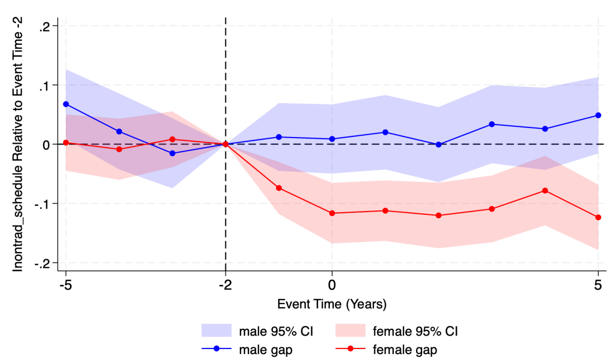
Figure 5: Event Study of Child's Impacts on Labor Supply



(a) employed



(b) work fulltime, cond. employed



(c) work non-dayshift, cond. employed

$$y^g_{ist} = \sum_{j \neq -2} \alpha^g_j \mathbf{I}(j = t) + \lambda^g_i + \gamma^g_s + \mathbb{X}^{g'}_{ist}\beta + \mu^g_{ist} \tag{26}$$

Figure 5 analyses the child impacts on labor supply using the event study approach with the NLSY97 Round 1 (1997-1998) through Round 19 (2019-2020) data.[35] Following Kleven et al. [2019], $t = 0$ is the year when the individual has the first child; event time goes from

[35]This analysis only focuses on the periods after the participant's ages above 18

five years before the birth to five years after the birth. Period $t = -2$ is omitted, and all the child impacts are compared with the period before pregnancy. g is the gender of the individual, and the regressions are run separately for males and females. Indicator dependent variables of interest for individual i in year s at event time t include extensive margin of labor supply, employed or not $\mathbf{I}(employed)$, and intensive margins of labor supply, whether working full-time $\mathbf{I}(fulltime)$ and whether working any non-day-shift schedule $\mathbf{I}(nontrad)$. When running regressions for $\mathbf{I}(employed)$, independent variables that are under control include individual, age, education, year, and region fixed effects. When running regressions for $\mathbf{I}(fulltime)$ and $\mathbf{I}(nontrad)$, I additionally control for industry and occupation fixed effects.

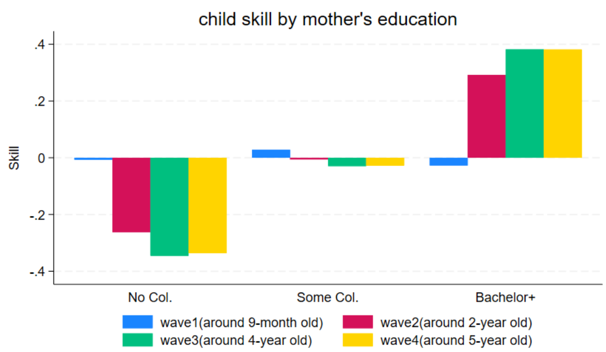
Consistent with the literature, childbirth decreases the mother's labor supply and barely has any impact on the father's labor supply. This is true both at the extensive margin and intensive margin. Referring to the schedule arrangement change, after having the child, the mother is around 10% less likely to work a non-day-shift schedule but there is no impact on the father's schedule arrangement. Based on these facts, this paper focuses on how the mother deals with the labor supply and care arrangement conflicts.

C Child's Skill Development by Different Subgroups

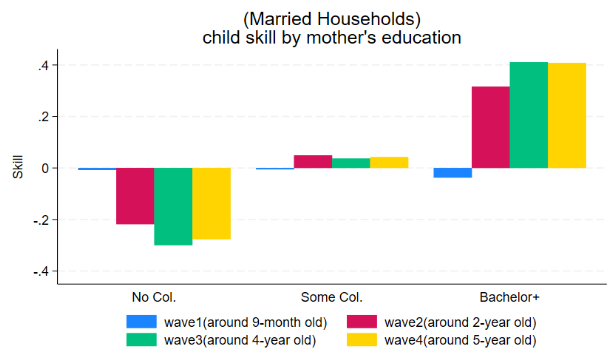
C.1 Skill Development by Mother's Education

Using the Early Childhood Longitudinal Study-Birth Cohort (ECLS-B) data, Figure 6 and Figure 7 show that children from different SES households exhibit similar skills at around nine months old. This is true both at the aggregate skill level and at the sub-skill level, which is measured through cognitive skill, physical skill, and social-emotional skill. The skill gap emerges later in the survey when children are around two years old and after. By the time of wave 4, when the children are around five years old (around kindergarten age), the average aggregate skill gap between children from households with non-college degree mothers and children from households with bachelor's degrees or higher mothers is around 0.7 standard deviation of the population skill at that wave.

Figure 6: Child skill development by mother's education



(a) For all households with mother present.

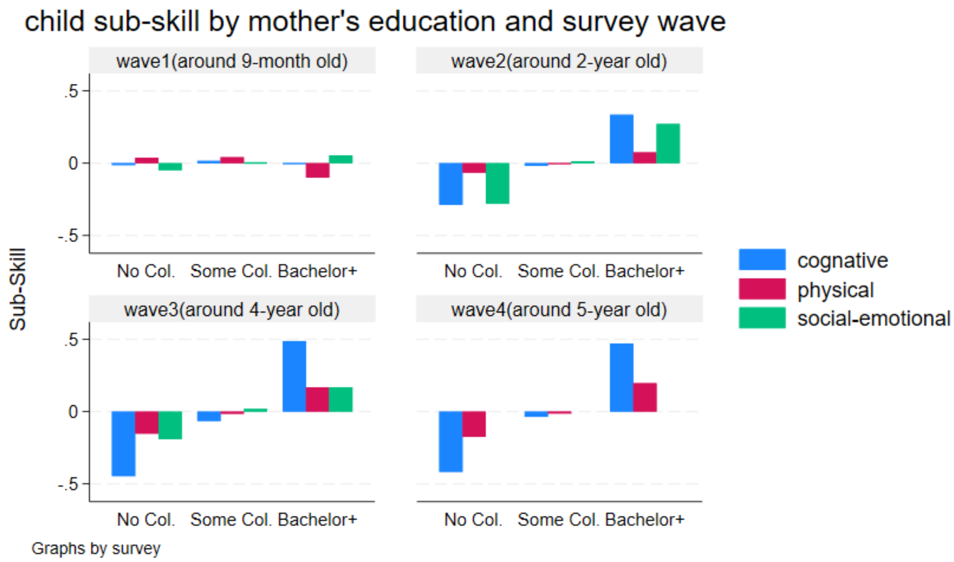


(b) For married household.

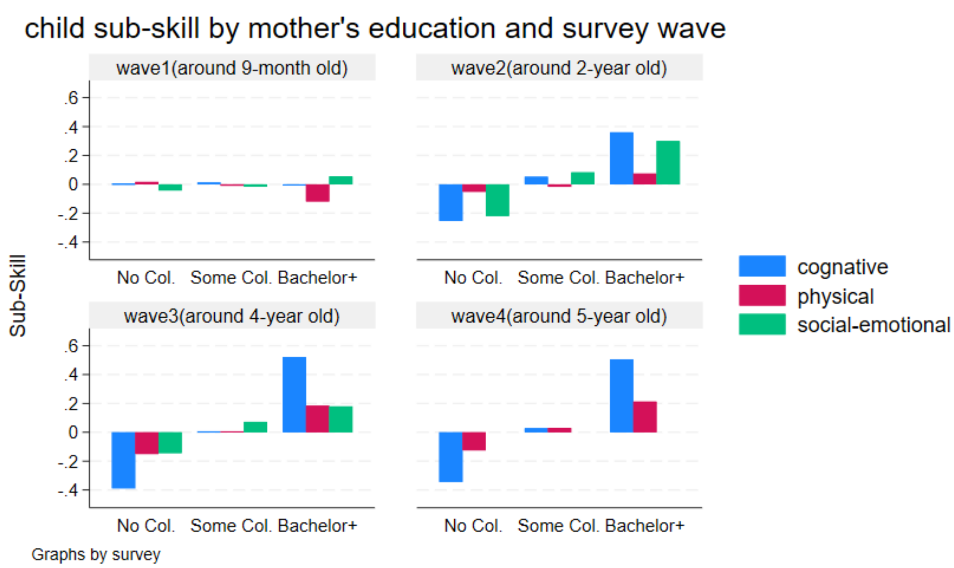
Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Notes: Skills are evaluated by multiple measurements, including Bayley Short Form-Research Edition (BSF-R), ECLS-B Cognitive and Physical Assessment Battery, Nursing Child Assessment Teaching Scale (NCATS), and Two Bags Task.

Figure 7: Child sub-skills development by mother's education



(a) For all households with mother present.



(b) For married household.

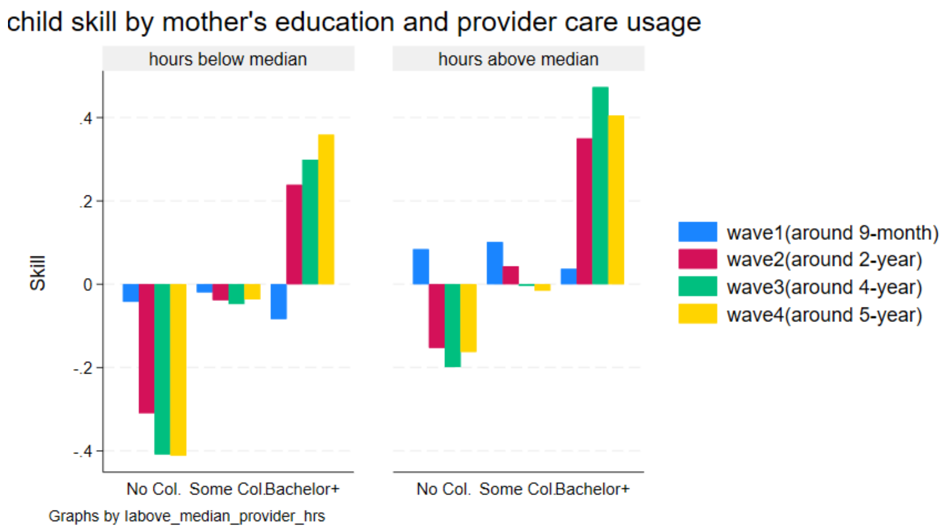
Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Notes: Sub-skills are evaluated by multiple measurements, including Bayley Short Form-Research Edition (BSF-R), ECLS-B Cognitive and Physical Assessment Battery, Nursing Child Assessment Teaching Scale (NCATS), and Two Bags Task.

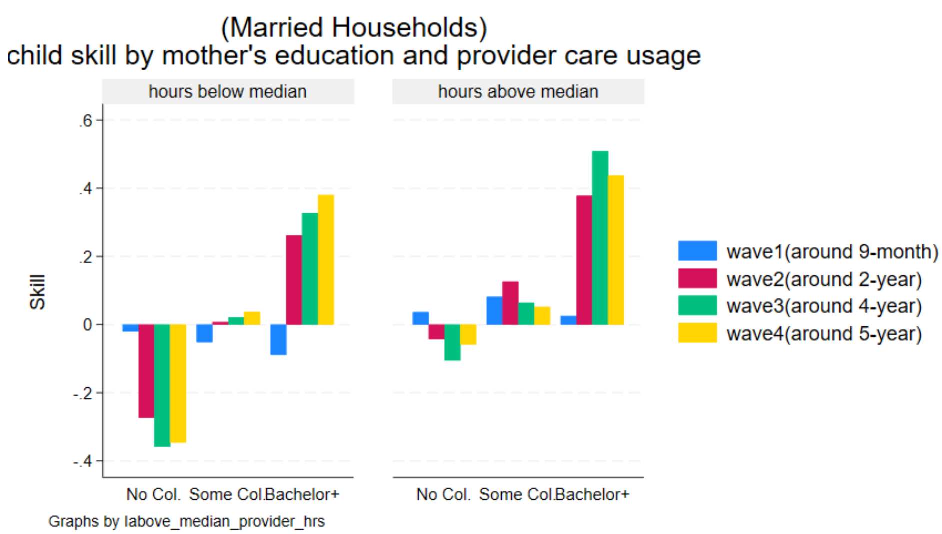
C.2 Skill Development by Care Intensity

Though care usage is quite endogenous, which depends on the quality and price of care that are drawn by the household and household's income, Figure 8 and Figure 9 roughly reveal the correlation between care usage and skill development. In Figure 8, from the Early Childhood Longitudinal Study-Birth Cohort (ECLS-B) data, more intensive usage of provider care is revealed to be associated with relatively higher aggregate skill. This association exists across waves, across mother's education groups, and across different marital statuses of the household. While more intensive usage of relative care is mainly associated with relatively lower aggregate skill.

Figure 8: Child skill development by mother's education and provider care usage



(a) For all households with mother present.

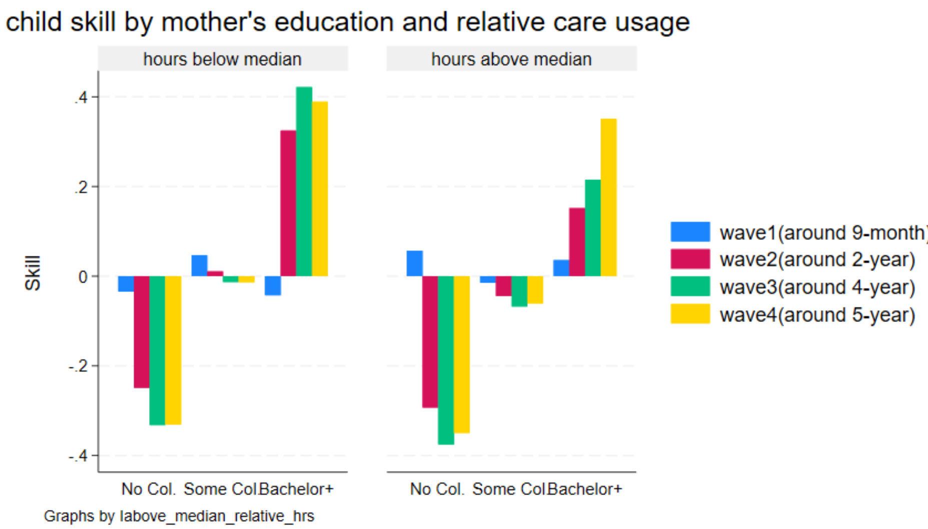


(b) For married household.

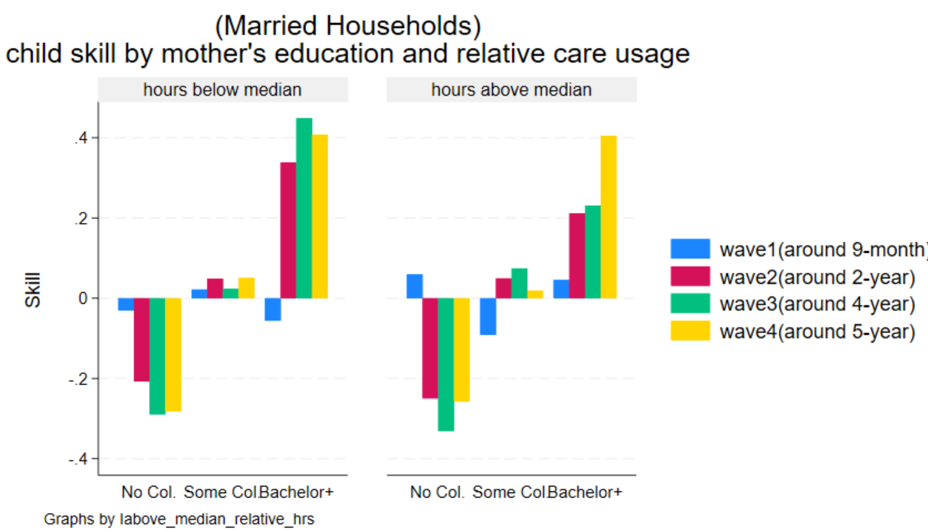
Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Notes: Skills are evaluated by multiple measurements, including Bayley Short Form-Research Edition (BSF-R), ECLS-B Cognitive and Physical Assessment Battery, Nursing Child Assessment Teaching Scale (NCATS), and Two Bags Task. Hours are calculated based on the primary care usage.

Figure 9: Child skill development by mother's education and relative care usage



(a) For all households with mother present.



(b) For married household.

Source: US Department of Education (2001–2006), National Center for Education Statistics, Early Childhood Longitudinal Study, Birth Cohort (ECLS-B).

Notes: Skills are evaluated by multiple measurements, including Bayley Short Form-Research Edition (BSF-R), ECLS-B Cognitive and Physical Assessment Battery, Nursing Child Assessment Teaching Scale (NCATS), and Two Bags Task. Hours are calculated based on the primary care usage.

D Computational Details

This section gives more explanations of the computational process. Based on the household's utility function, all the constraints, the endowed information set

$$\Phi = \{h_0, \epsilon_h, \epsilon_w, \epsilon^q_{parent}, I_r^{available}, I_r^{free}, I_r^{nstd}, \epsilon^q_r, \epsilon^p_r, \epsilon^q_{ps}, \epsilon^p_{ps}, \epsilon^q_{pa}, \epsilon^p_{pa}, E^s, E^{hs}\},$$

the model can be simplified as follows.

$$\begin{aligned}
\max U = &\ln\Big\{ \overbrace{\underbrace{Y + I_{father} + \underbrace{\exp\{\alpha_w^{edu} ns_m^{work} + \boldsymbol{X'\beta_w} + \epsilon_w\}}_{w} L_m}_{hhinc} - \tau_r p_r - C_c^p}^{C_{hh}} \Big\} \\
&+ \gamma_{l_m} \ln\{\overbrace{T - T_c + \tau_f + \tau_r + \tau_p - L_m}^{l_m}\} + \gamma_{l_f} \ln\{\overbrace{T - \overline{L_f} - \tau_f}^{l_f}\} \\
&+ \gamma_{h_1} \Big\{ \underbrace{\delta_0 + \delta_1 \ln h_0 + \delta_{parent} \frac{\overbrace{T_c - \tau_r - \tau_p}^{\tau_{parent}}}{T_c} q_{parent} + \delta_r \frac{\tau_r}{T_c} q_r + \delta_p \big(\frac{\tau_p^{std}}{T_c} q_p^{std} + \frac{\tau_p^{nstd}}{T_c} q_p^{nstd}\big)}_{\ln h_1} \Big\} \\
&+ \gamma_{parent} \ln\{\overbrace{T_c - \tau_r - \tau_p}^{\tau_{parent}}\} \\
s.t. \quad &\overbrace{(1 - ns_f^{care})\tau_f}^{\tau_f^{std}} \le T^{std} - \overline{L_f^{std}}, \text{ i.e. } l_f^{std} \ge 0 \\
&\overbrace{ns_f^{care}\tau_f}^{\tau_f^{nstd}} \le T^{nstd} - \overline{L_f^{nstd}}, \text{ i.e. } l_f^{nstd} \ge 0 \\
&\overbrace{(1 - ns_m^{work})L_m}^{L_m^{std}} \le (1 - ns_f^{care})\tau_f + \tau_r^{std} + \tau_p^{std} \le T_c^{std}, \\
&\overbrace{ns_m^{work} L_m}^{L_m^{nstd}} \le ns_f^{care}\tau_f + \tau_r^{nstd} + \tau_p^{nstd} \le T_c^{nstd}, \\
&\text{(The above constraints are necessary since there is no separate preference for } l_m^{std} \text{ and } l_m^{nstd}) \\
&ns_m^{work}, ns_f^{care} \in [0, 1], \\
&L_m, \tau_f, \tau_r^{std}, \tau_r^{nstd}, \tau_p^{std}, \tau_p^{nstd} \ge 0, \\
&C_c^p = (1 - E^s(I^S = 1))\Big[\big(1 - E^{hs}(P^{std} = ps)\big)\min\{\tau_p^{std}, \bar{h}^{hs}\}p_p^{std} + \max\{0, \tau_p^{std} - \bar{h}^{hs}\}p_p^{std} + \tau_p^{nstd}p_p^{nstd}\Big] \\
&\qquad + E^s(I^S = 1)\Big[\psi \times hhinc + \big(1 - E^{hs}(P^{std} = ps)\big)\min\{\tau_p^{std}, \bar{h}^{hs}\}(p_p^{std} - rc)I\{p_p^{std} > rc\} \\
&\qquad\qquad + \max\{0, \tau_p^{std} - \bar{h}^{hs}\}(p_p^{std} - rc)I\{p_p^{std} > rc\} \\
&\qquad\qquad + \tau_p^{nstd}(p_p^{nstd} - rc)I\{p_p^{nstd} > rc\}\Big]
\end{aligned}$$

First order condition for non-parental care, regardless of constraints.

$$\begin{aligned}
\text{F.O.C}\quad [\tau_r^{std}]: &\quad -\frac{p_r}{C_{hh}} + \frac{\gamma_{l_m}}{l_m} + \gamma_{h_1}\frac{\delta_r q_r}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} && (27)\\
[\tau_r^{nstd}]: &\quad -\frac{p_r}{C_{hh}} + \frac{\gamma_{l_m}}{l_m} + \gamma_{h_1}\frac{\delta_r q_r}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} && (28)\\
[\tau_p^{std}]: &\quad -\frac{\widetilde{p_p^{std}}}{C_{hh}} + \frac{\gamma_{l_m}}{l_m} + \gamma_{h_1}\frac{\delta_p q_p^{std}}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} && (29)\\
[\tau_p^{nstd}]: &\quad -\frac{\widetilde{p_p^{nstd}}}{C_{hh}} + \frac{\gamma_{l_m}}{l_m} + \gamma_{h_1}\frac{\delta_p q_p^{nstd}}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} && (30)
\end{aligned}$$

where first order condition depends on $\tau_p^{std} \leq$ or $> \bar{h}^{hs}$. Define $\pi \equiv E^{hs}(P^{std} = ps)$, $\pi = 1$ means household has access to HS and the provider is a HS granted provider, $\pi = 0$ means household has no access to HS or the provider is not a HS granted provider. For the convenience of writing, further define $\Omega \equiv 1 - \pi(\tau_p^{std} < \bar{h}^{hs})$.

$$\begin{aligned}
\widetilde{p_p^{std}} =& \Omega\big[(1 - E^s(I^S = 1))p_p^{std} + E^s(I^S = 1)(p_p^{std} - rc)I\{p_p^{std} > rc\}\big] \equiv \Omega\widehat{p_p^{std}}\\
\widetilde{p_p^{nstd}} =& (1 - E^s(I^S = 1))p_p^{nstd} + E^s(I^S = 1)(p_p^{nstd} - rc)I\{p_p^{nstd} > rc\}
\end{aligned}$$

Therefore, childcare costs can be rearranged as,

$$\begin{aligned}
C_c^p =& \widetilde{p_p^{std}}\tau_p^{std} + \widetilde{p_p^{nstd}}\tau_p^{nstd} + ccp\\
ccp \equiv& E^s(I^S = 1)\psi \times hhinc - \pi(\tau_p^{std} > \bar{h}^{hs})\bar{h}^{hs}\widehat{p_p^{std}}
\end{aligned}$$

D.1 Mixed Analytic and Numerical Solution

For computational tractability, assume that within standard hours or nonstandard hours, the household only uses one type of nonparental provider. During standard hours, the household chooses between relative and two types of providers and is not allowed to use both at the same time; and the same rule applies to nonstandard hours.

Therefore, the first order conditions (27)-(30) above can be simplified as follows,

$$\begin{aligned}
\text{F.O.C}\quad [\tau_j^{std}] &\quad -\frac{\widetilde{p_j^{std}}}{C_{hh}} + \frac{\gamma_{l_m}}{l_m} + \gamma_{h_1}\frac{\delta_j q_j^{std}}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} = 0, \quad \text{where } j \in \{ps, pa, r\} && (31)\\
[\tau_k^{nstd}] &\quad -\frac{\widetilde{p_k^{nstd}}}{C_{hh}} + \frac{\gamma_{l_m}}{l_m} + \gamma_{h_1}\frac{\delta_k q_k^{nstd}}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} = 0, \quad \text{where } k \in \{pa, r\} && (32)
\end{aligned}$$

Based on whether relatives are available and willing to provide care, $j \times k \equiv \{ps, pa, r\} \times \{pa, r\}$ can have 2 possible combinations if relative care is unavailable; or 6 possible combinations if relative care is available. For writing convenience, $\widetilde{p_r^{std}} \equiv p_r$ and $\widetilde{p_r^{nstd}} \equiv p_r$. For each of the cases, use the following steps to find the optimal solution.

Since mother's labor choices L_m, ns_m^{work} are constrained by care choices and since how father's time is distributed to paternal care τ_f and among standard and nonstandard hours ns_f^{care} can easily change the boundary; due to the complication of the boundary settings, it is impossible to write out clear analytical solutions for all the choices. The model is solved through a mixed analytic and numerical strategy. In the model, I perform a grid search over the maternal labor choices and paternal care choices, and the childcare usage is solved using the first-order condition given the maternal labor and paternal care management.

In the model, the mother chooses whether not to work, to work half time, or to work full time, $L_m \in \{0, 20, 40\}$. The nonstandard fraction of maternal labor supply, $ns_m^{work} \equiv \frac{L_m^{nstd}}{L_m}$, $ns_m^{work} \in \{0.0, 0.11, 0.52, 0.90\}$ for half-time workers and $ns_m^{work} \in \{0.0, 0.09, 0.23, 0.49\}$ for full-time workers.[36] Based on the time constraints, paternal care needs to meet the following requirements.

$$(1 - ns_f^{care})\tau_f \leq \min\{T^{std} - \overline{L_f^{std}}, T_c^{std}\} \tag{33}$$

$$ns_f^{care}\tau_f \leq \min\{T^{nstd} - \overline{L_f^{nstd}}, T_c^{nstd}\} \tag{34}$$

The range of τ_f is based on the population distribution. Suppose τ_f is known, ns_f^{care} is searched over the following range.

$$\max\Big\{0, 1 - \frac{\min\{T^{std} - \overline{L_f^{std}}, T_c^{std}\}}{\tau_f}\Big\} \leq ns_f^{care} \leq \min\Big\{1, \frac{\min\{T^{nstd} - \overline{L_f^{nstd}}, T_c^{nstd}\}}{\tau_f}\Big\} \tag{35}$$

D.1.1 Suppose I^S, L_m, ns_m^{work}, τ_f, ns_f^{care}, and type of providers are known, and both τ_j^{std} and τ_k^{nstd} are interior solutions

I firstly check the sign of C_{hh}, $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{F}$ first. If $C_{hh} < 0$ or $\boldsymbol{A} < 0$ or $\boldsymbol{B} < \max\{0, L_m - \tau_f\}$ or $\boldsymbol{B} > T_c - \tau_f$ or $\boldsymbol{F} < 0$, move on to Section D.1.2 and Section D.1.3.

$$\begin{cases} \text{Equations (31) and (32)} & \Rightarrow C_{hh} = \frac{(\widetilde{p_j^{std}} - \widetilde{p_k^{nstd}})T_c}{(\delta_j q_j^{std} - \delta_k q_k^{nstd})\gamma_{h_1}} \quad \text{is constant with given information} \\ \text{Budget constraints} & \Rightarrow C_{hh} = hhinc - \tau_j^{std}\widetilde{p_j^{std}} - \tau_k^{nstd}\widetilde{p_k^{nstd}} - ccp \\ \text{Equations (31)} & \Rightarrow l_m = \gamma_{l_m}\Big(\underbrace{\frac{\widetilde{p_j^{std}}}{C_{hh}} - \gamma_{h_1}\frac{\delta_j q_j^{std}}{T_c}}_{\equiv \boldsymbol{D}} + \frac{\gamma_{parent}}{\tau_{parent}}\Big)^{-1} \\ \text{Time constraints} & \Rightarrow l_m = \underbrace{T_M + \tau_f - L_m}_{\equiv \boldsymbol{E}} - \tau_{parent}, \quad \text{where } \tau_{parent} = T_c - \tau_j^{std} - \tau_k^{nstd} \end{cases}$$

[36] $\{0.0, 0.11, 0.52, 0.90\}$ are the 25%, 50%, 75% and 90% quantile of the schedule distribution for half-time workers; and $\{0.0, 0.09, 0.23, 0.49\}$ are the 25%, 50%, 75% and 90% quantile of the schedule distribution for full-time workers.

$$\Rightarrow \begin{cases} \tau_j^{std}\widetilde{p_j^{std}} + \tau_k^{nstd}\widetilde{p_k^{nstd}} & = \underbrace{hhinc - ccp - C_{hh}}_{\equiv \boldsymbol{A}}, \quad \text{where } C_{hh} = \frac{(\widetilde{p_j^{std}} - \widetilde{p_k^{nstd}})T_c}{(\delta_j q_j^{std} - \delta_k q_k^{nstd})\gamma_{h_1}} \\ \tau_j^{std} + \tau_k^{nstd} & = \underbrace{T_c + \frac{(\gamma_{parent} + \gamma_{l_m} - \boldsymbol{DE}) \pm \sqrt{\underbrace{(\gamma_{parent} + \gamma_{l_m} - \boldsymbol{DE})^2 + 4\boldsymbol{DE}\gamma_{parent}}_{\equiv \boldsymbol{F}}}}{2\boldsymbol{D}}}_{\equiv \boldsymbol{B}} \end{cases}$$

$$\Rightarrow \begin{cases} \tau_j^{std} = \frac{A - B\widetilde{p_k^{nstd}}}{\widetilde{p_j^{std}} - \widetilde{p_k^{nstd}}} \\ \tau_k^{nstd} = \frac{B\widetilde{p_j^{std}} - A}{\widetilde{p_j^{std}} - \widetilde{p_k^{nstd}}} \end{cases}$$

After obtaining the value of τ_j^{std} and τ_k^{nstd}, recheck if the constraints are satisfied. When $\pi = 0$, no access to HS, boundaries need to meet the following constraints. When $\pi = 1$, boundaries are adjusted based on the original assumption of whether τ_j^{std} is below or above $\bar{h}^{hs}$.

$$\Rightarrow \begin{cases} \text{if } \tau_j^{std} < \max\{0, L_m^{std} - \tau_f^{std}\} & \Rightarrow \text{Section D.1.2 with } \tau_j^{std} = \max\{0, L_m^{std} - \tau_f^{std}\} \\ \text{if } \tau_j^{std} > T_c^{std} - \tau_f^{std} & \Rightarrow \text{Section D.1.2 with } \tau_j^{std} = T_c^{std} - \tau_f^{std} \\ \text{if } \tau_k^{nstd} < \max\{0, L_m^{nstd} - \tau_f^{nstd}\} & \Rightarrow \text{Section D.1.3 with } \tau_k^{nstd} = \max\{0, L_m^{nstd} - \tau_f^{nstd}\} \\ \text{if } \tau_k^{nstd} > T_c^{nstd} - \tau_f^{nstd} & \Rightarrow \text{Section D.1.3 with } \tau_k^{nstd} = T_c^{nstd} - \tau_f^{nstd} \end{cases}$$

If two of the above constraints are violated, this situation is included in the following discussion.

D.1.2 Suppose I^S, L_m, ns_m^{work}, τ_f, ns_f^{care}, and type of providers are known, τ_j^{std} is on the boundary, and τ_k^{nstd} are inner solution

Given τ_f, ns_f^{care}, L_m and ns_m^{work}, when τ_j^{std} is on the boundary, $\tau_j^{std} \in \{0, L_m^{std} - \tau_f^{std}\}$ which depends on the discussion above.

Based on equation (32):

$$-\frac{\widetilde{p_k^{nstd}}}{C_{hh}} + \frac{\gamma_{l_m}}{l} + \gamma_{h_1}\frac{\delta_k q_k^{nstd}}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} = 0$$

$$\Rightarrow \quad \frac{1}{\underbrace{\frac{-hhinc + \tau_j^{std}\widetilde{p_j^{std}}}{\widetilde{p_k^{nstd}}}}_{\equiv \boldsymbol{G}} + \tau_k^{nstd}} + \frac{\gamma_{l_m}}{\underbrace{T_M - T_c - L_m + \tau_f + \tau_j^{std}}_{\equiv \boldsymbol{H}} + \tau_k^{nstd}} + \frac{\gamma_{parent}}{\underbrace{-T_c + \tau_j^{std}}_{\equiv \boldsymbol{I}} + \tau_k^{nstd}} + \underbrace{\gamma_{h_1}\frac{\delta_k q_k^{nstd}}{T_c}}_{\equiv \boldsymbol{J}} = 0$$

$$\Rightarrow J(\tau_k^{nstd})^3$$
$$+ [1 + \gamma_{l_m} + \gamma_{parent} + J(G + H + I)](\tau_k^{nstd})^2$$

$$+ [(H+I) + \gamma_{l_m}(G+I) + \gamma_{parent}(G+H) + J(GH+GI+HI)]\tau_k^{nstd}$$
$$+ HI + \gamma_{l_m} GI + \gamma_{parent} GH + GHIJ = 0$$

This is a cubic function with one unknown, τ_k^{nstd}. After solving the model, check the following restrictions.

$$\begin{cases} \text{if } \tau_k^{nstd} < \max\{0, L_m^{nstd} - \tau_f^{nstd}\} & \Rightarrow \tau_k^{nstd} = \max\{0, L_m^{nstd} - \tau_f^{nstd}\} \\ \text{if } \tau_k^{nstd} > T_c^{nstd} - \tau_f^{nstd} & \Rightarrow \tau_k^{nstd} = T_c^{nstd} - \tau_f^{nstd} \\ \text{if no solution} & \Rightarrow \tau_k^{nstd} = \left\{ \max\{0, L_m^{nstd} - \tau_f^{nstd}\}, T_c^{nstd} - \tau_f^{nstd} \right\} \end{cases}$$

D.1.3 Suppose I^S, L_m, ns_m^{work}, τ_f, ns_f^{care}, τ_k^{nstd}, and type of providers are known, and τ_j^{std} are inner solution

Given L_m^{std} and L_m^{nstd}, when τ_k^{nstd} is on the boundary, $\tau_k^{nstd} \in \{0, L_m^{nstd} - \tau_f^{nstd}\}$ which depends on the discussion above.

Based on equation (31):

$$-\frac{\widetilde{p_j^{std}}}{C_{hh}} + \frac{\gamma_{l_m}}{l} + \gamma_{h_1}\frac{\delta_j q_j^{std}}{T_c} - \frac{\gamma_{parent}}{\tau_{parent}} = 0$$

$$\Rightarrow \frac{1}{\underbrace{\frac{-hhinc + \tau_k^{nstd}\widetilde{p_k^{nstd}}}{\widetilde{p_j^{std}}}}_{\equiv \boldsymbol{G}} + \tau_j^{std}} + \frac{\gamma_{l_m}}{\underbrace{T_M - T_c + \tau_f - L_m + \tau_k^{nstd}}_{\equiv \boldsymbol{H}} + \tau_j^{std}} + \frac{\gamma_{parent}}{\underbrace{-T_c + \tau_k^{nstd}}_{\equiv \boldsymbol{I}} + \tau_j^{std}} + \gamma_{h_1}\underbrace{\frac{\delta_j q_j^{std}}{T_c}}_{\equiv \boldsymbol{J}} = 0$$

$$\Rightarrow J(\tau_j^{std})^3$$
$$+ [1 + \gamma_{l_m} + \gamma_{parent} + J(G+H+I)](\tau_j^{std})^2$$
$$+ [(H+I) + \gamma_{l_m}(G+I) + \gamma_{parent}(G+H) + J(GH+GI+HI)]\tau_j^{std}$$
$$+ HI + \gamma_{l_m} GI + \gamma_{parent} GH + GHIJ = 0$$

This is a cubic function with one unknown, τ_j^{std}. After solving the model, check the following restrictions and reset the value if necessary. When $\pi = 0$, no access to HS, boundaries need to meet the following constraints. When $\pi = 1$, boundaries are adjusted based on the original assumption of whether τ_j^{std} is below or above $\bar{h}^{hs}$.

$$\begin{cases} \text{if } \tau_j^{std} < \max\{0, L_m^{std} - \tau_f^{std}\} & \Rightarrow \tau_j^{std} = \max\{0, L_m^{std} - \tau_f^{std}\} \\ \text{if } \tau_j^{std} > T_c^{std} - \tau_f^{std} & \Rightarrow \tau_j^{std} = T_c^{std} - \tau_f^{std} \\ \text{if no solution} & \Rightarrow \tau_j^{std} = \left\{ \max\{0, L_m^{std} - \tau_f^{std}\}, T_c^{std} - \tau_f^{std} \right\} \end{cases}$$

D.2 Counterfactual setting

In the counterfactual where HS is applied to both providers who only operate during standard hours ps and providers who operate during both standard and nonstandard hours pa, π is defined as $\pi \equiv E^{hs}$. When additional relaxation, allowing HS to be used in both standard hours and nonstandard hours, is made, define $\Omega' \equiv 1 - \pi(\tau_p^{nstd} < \bar{h}^{hs})$ and redefine $\widetilde{p_p^{std}}$ and $\widetilde{p_p^{nstd}}$ in the following way,

$$
\begin{aligned}
\widetilde{p_p^{std}} =& \Omega\big[(1 - E^s(I^S = 1))p_p^{std} + E^s(I^S = 1)(p_p^{std} - rc)I\{p_p^{std} > rc\}\big] \equiv \Omega\widehat{p_p^{std}} \\
\widetilde{p_p^{nstd}} =& \Omega'\big[(1 - E^s(I^S = 1))p_p^{nstd} + E^s(I^S = 1)(p_p^{nstd} - rc)I\{p_p^{nstd} > rc\}\big] \equiv \Omega'\widehat{p_p^{nstd}}
\end{aligned}
$$

Childcare cost is rearranged as,

$$
\begin{aligned}
C_c^p =& \widetilde{p_p^{std}}\tau_p^{std} + \widetilde{p_p^{nstd}}\tau_p^{nstd} + ccp \\
ccp \equiv& E^s(I^S = 1)\psi \times hhinc - \pi(\tau_p^{std} > \bar{h}^{hs})\bar{h}^{hs}\widehat{p_p^{std}} - \pi(\tau_p^{nstd} > \bar{h}^{hs})\bar{h}^{hs}\widehat{p_p^{nstd}}
\end{aligned}
$$

Household problems are solved in similar ways as discussed above.

D.3 Settings for Total Weekly Childcare Demand

Based on the study of Iglowstein et al. [2003], nighttime sleep duration for children age from 0 to 4 ranges from 11.0 to 11.7 hours; based on the study of Galland et al. [2012], mean sleep duration for infants is 12.8 hours, and for toddler/preschool is 11.9 hours; and referring to Chaparro et al. [2020], I assume the child in the model needs 11.5 hours of sleep every night during which no care is needed. Therefore, the total amount of care hours that are needed each week, T_c, are equal to 87.5 hours.[37]

Defining standard hours as hours from 8 a.m. to 6 p.m. on Monday through Friday, the maximum number of standard hours the family can use, T_c^{std}, are 50 hours. If denote this maximum amount as T_c^{std}. All hours outside of 8 a.m. to 6 p.m. are defined as nonstandard hours. Based on the assumption that T_c can not exceed 87.5 hours, the maximum number of nonstandard hours of care that is potentially needed every week, T_c^{nstd}, can not exceed 37.5 hours.[38]

E Estimation Results

Table 25 shows that the quality of providers who operate any schedule, on average, is around 1.158 standard deviations lower than that of providers who provide service only during

[37] $T_c = 24 * 7 - 11.5 * 7 = 87.5$ hrs

[38] $T_c^{nstd} = T_{tot} - T_c^{std} = 87.5 - 50 = 37.5$ hrs

standard hours. This is true for all the educationXrace subgroups.

Table 25: Quality gap btw any-schedule providers(pa) and standard-hour-only providers(ps)

	$q_{pa} - q_{ps}$		
	white	black	other
no college	-1.312	-1.051	-1.447
some college	-0.985	-0.724	-1.121
bachelor	-1.304	-1.043	-1.440
average	-1.158		

F Identification

F.1 Moments for Identification

This section elaborates on how each parameter is identified by different moments.

1. **probability of relative care being available during nonstandard hours**

   (a) **Moments**: Conditional on using relative care, what proportion of households use any relative care among nonstandard hours.

2. **probability of free relative care**

$$Pr_r^{free}(\boldsymbol{I}_r^{free} = 1|\boldsymbol{Z}) = \frac{1}{1 + e^{-(\delta_{f0}^{free} + \boldsymbol{Z'}\boldsymbol{\delta}_f^{free})}} \tag{36}$$

   (a) **Moments**: Proportion of free relative care, $\boldsymbol{I}_r^{free}$, among different education, race, and marriage groups.

3. **quality distribution**

$$q_j = \gamma_{j0} + \gamma_j^{edu} + \gamma_j^{race} + E^{hs}\gamma_{j=ps}^{hs} + \epsilon_j^q \quad \text{where } j \in \{parent, r, ps, pa\} \tag{37}$$

   (a) Parental care quality is estimated outside of the model.

   (b) **Moments**: Indirect inference by running the regressions for $\{q_r$, q_{ps}, q_{pa}, $q_{parent}\}$.

   (c) **Moments**: Compare quality of care, $\{q_r, q_{p_{prim}}, q_{parent}\}$, among different education, race and marriage groups. And compare $q_{p_{prim}}$ based on operation time, where $q_{p_{prim}}$ is the quality of the primary care used for the child.

4. **price function**

$$\ln p_k = \beta_{k0} + \beta_{k1} q_k + \epsilon_k^p \qquad \text{where } k \in \{f, ps, pa\} \tag{38}$$

(a) **Moments**: Indirect inference by running the skill production regressions.

(b) **Moments**: Compare the price of relative and provider care among different education, race, marriage, and operation groups.

5. **skill production function**

$$\begin{aligned}\ln h_1 =& \delta_0 + \delta_1 \ln h_0 \\ &+ \sum_{i \in \{std, nstd\}} \Big\{ \delta_{parent}(h_0) \frac{\tau_m^i + \tau_f^i}{T_c} \ln q_{parent} + \delta_r(h_0) \frac{\tau_r^i}{T_c} \ln q_r + \delta_p(h_0) \frac{\tau_p^i}{T_c} \ln q_p \Big\} + \epsilon_h\end{aligned} \tag{39}$$

(a) **Moments**: Indirect inference by running the skill production regression using ECLS-B data, where hours are average weekly hours and initial skill $\ln h_0$ is normalized to be with mean zero and standard error one. h_1 is the skill at age five.

(b) **Moments**: $\ln h_1$ by all, education, race, marriage, and operation time;

(c) **Moments**: $\ln h_1$, childcare usage, and childcare quality conditional on initial skill below or above median.

(d) **Moments**: Parental and non-parental childcare arrangement by type, education, race, and marriage.

(e) **Moments**: Labor supply by education, race, and marriage.

6. **Head Start Probability Function**

$$\pi_{hs} = \begin{cases} \dfrac{1}{1 + exp(-\gamma_0^{hs} - \gamma_1^{hs} I\{hhinc > \bar{y}^{hs}\})}, & \text{if } hhinc < 130\% \bar{y}^{hs}, \text{ eligible} \\ 0 & \text{, otherwise} \end{cases}$$

(a) **Moments:** In 2019, there were around 19.57 million children in the US aged under five, and around 0.87 million of them were enrolled in the HS programs.

(b) **Moments:** Conditional on there are unfilled spots, Head Start programs may enroll up to 10% of the total children from households with incomes over the poverty guidelines but beneath the 130% federal poverty level.[39]

[39] Administration for Children and Families.

7. **Utility Function**

   Preference for consumption: **Moments**: Childcare and labor supply decisions can help identify the preference for consumption.

   Preference for maternal leisure: **Moments**: Childcare arrangement and maternal labor arrangement can help identify the preference for maternal leisure.

   Preference for paternal leisure: **Moments**: The is identified through usage of paternal care, τ_f and ns_f^{care}.

   Preference for child's skill: **Moments**: This is identified through childcare arrangements. There might be concerns that preference for the child's skill and quality friction in the childcare market (or quality distribution) can not be jointly identified. Moments of childcare usage by marital status help the identification, since marital status does not enter the quality distribution function and it only affects skill through the household budget and paternal care choices.

   Preference for parental care: **Moments**: In reality, parental care hours are almost never zero, and parental care usage can help identify the preference for parental care.

8. **identification for variance and covariance**

   Variance covariance matrix of quality distribution.

   (a) **Moments**: Variance of quality by type, $var(q_r)$, $var(q_{ps})$, $var(q_{pa})$, $var(q_{parent})$.

   (b) **Moments**: Covariance between providers, $cov(q_{ps}, q_{pa})$.

   Variance covariance matrix of price distribution.

   (a) **Moments**: Variance of price by type, $var(p_r)$ $var(p_{ps})$ $var(p_{pa})$.

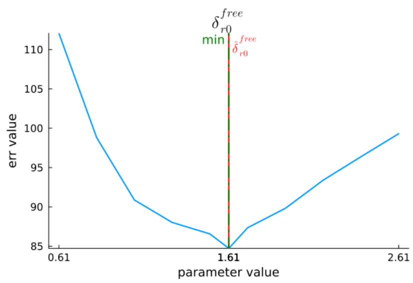
   (b) **Moments**: Covariance between providers, $cov(p_{ps}, p_{pa})$.

   Standard deviation of the skill production function.

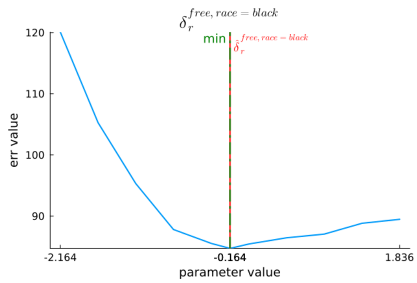
   (a) **Moments**: Variance of skill at the end of the period, $var(\ln h_1)$

Figure 10: Identification graphs

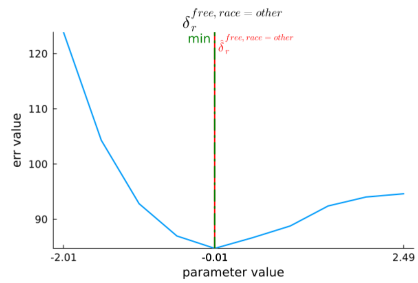
F.2 Identification Figures for Each Parameter



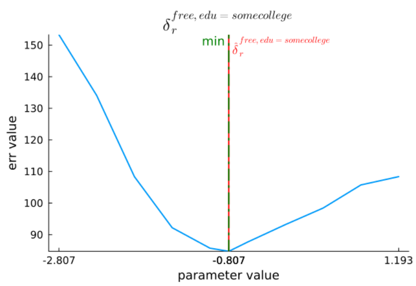
(a) δ_{r0}^{free}



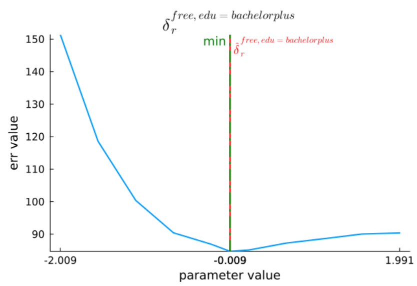
(b) $\delta_r^{free,race=black}$



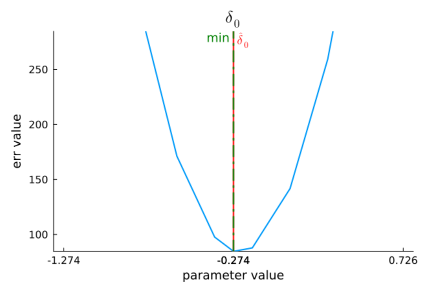
(c) $\delta_r^{free,race=other}$



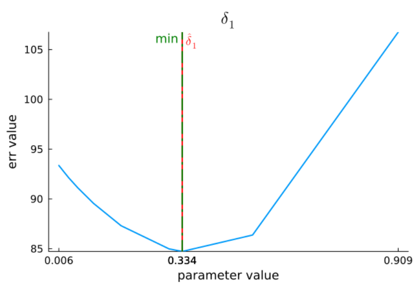
(d) $\delta_r^{free,edu=some\ college}$



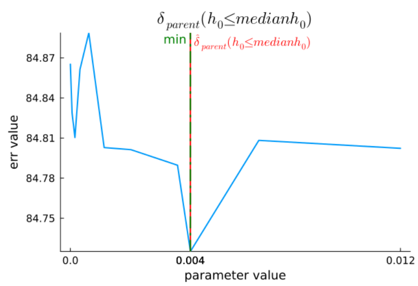
(e) $\delta_r^{free,edu=bachelor\ plus}$



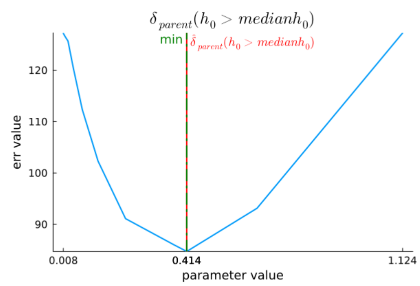
(f) δ_0



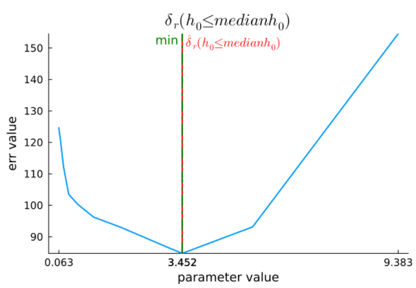
(g) δ_1



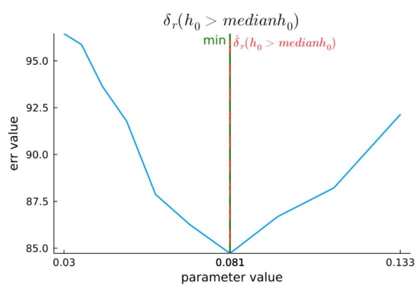
(h) $\delta_{parent}(h_0 \leq \bar{h_0})$



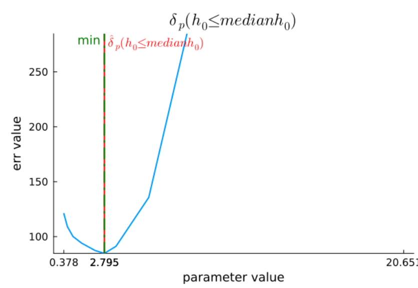
(i) $\delta_{parent}(h_0 > \bar{h_0})$



(j) $\delta_r(h_0 \leq \bar{h_0})$

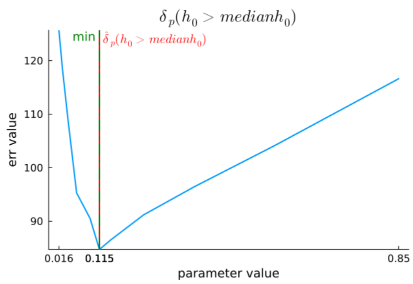


(k) $\delta_r(h_0 > \bar{h_0})$

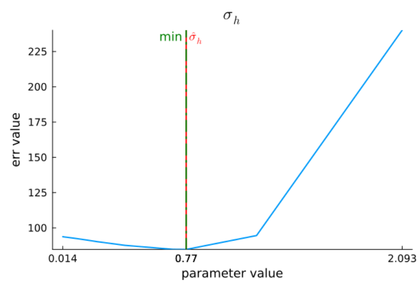


(l) $\delta_p(h_0 \leq \bar{h_0})$

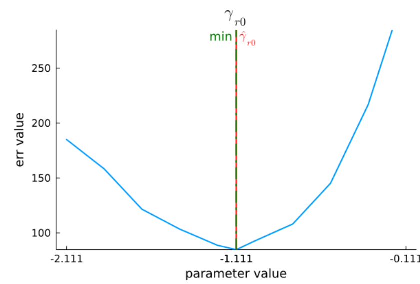
Figure 11: Identification graphs



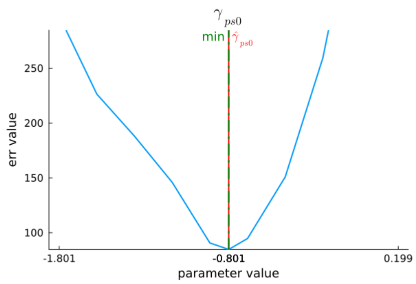
(a) $\delta_p(h_0 > \bar{h_0})$



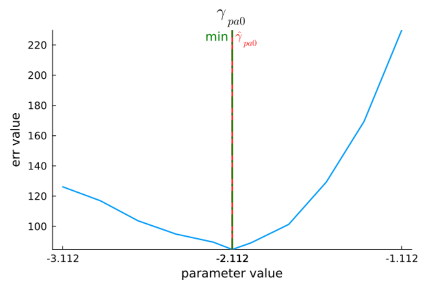
(b) σ_h



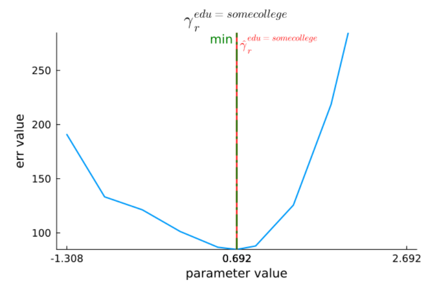
(c) γ_{r0}



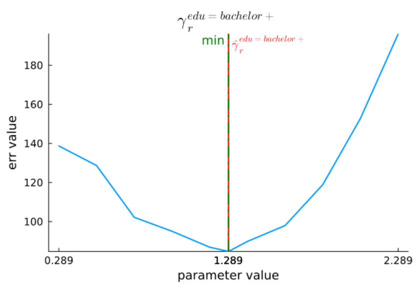
(d) γ_{ps0}



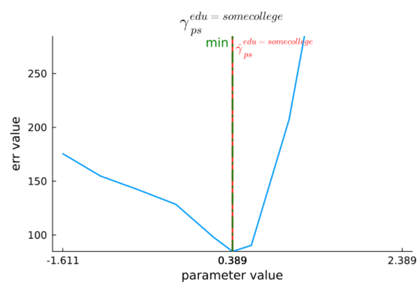
(e) γ_{pa0}



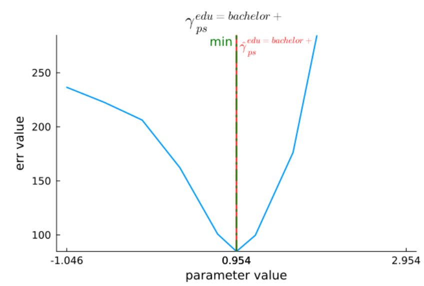
(f) $\gamma_r^{edu=some\ college}$



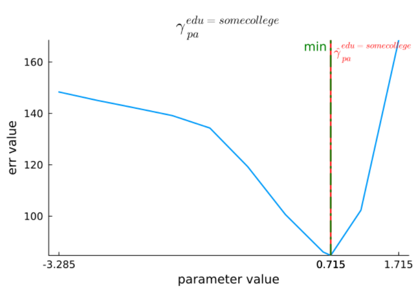
(g) $\gamma_r^{edu=bachelor\ plus}$



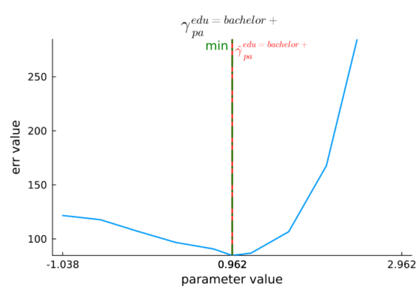
(h) $\gamma_{ps}^{edu=some\ college}$



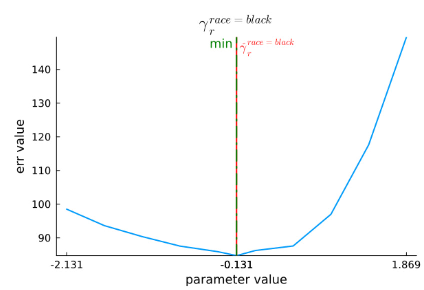
(i) $\gamma_{ps}^{edu=bachelor\ plus}$



(j) $\gamma_{pa}^{edu=some\ college}$

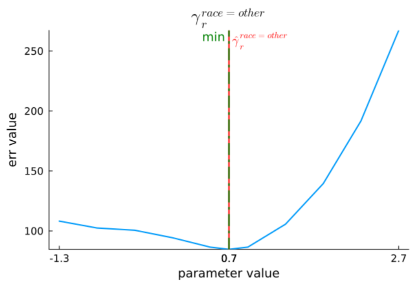


(k) $\gamma_{pa}^{edu=bachelor\ plus}$

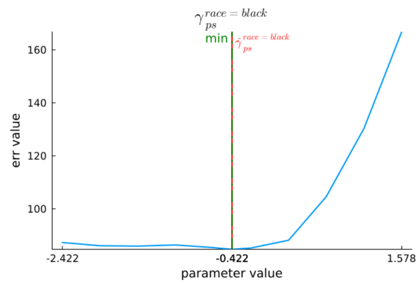


(l) $\gamma_r^{race=black}$

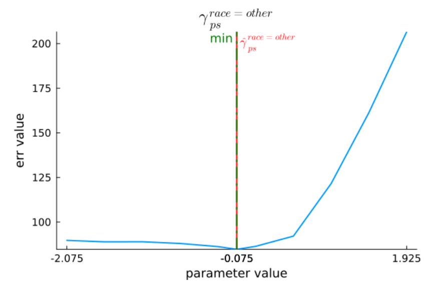
Figure 12: Identification graphs



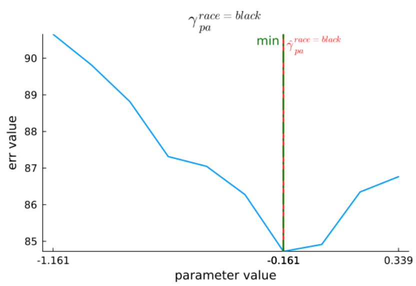
(a) $\gamma_r^{race=other}$



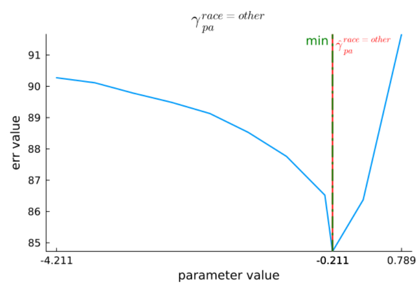
(b) $\gamma_{ps}^{race=black}$



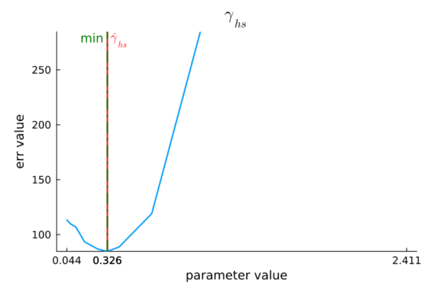
(c) $\gamma_{ps}^{race=other}$



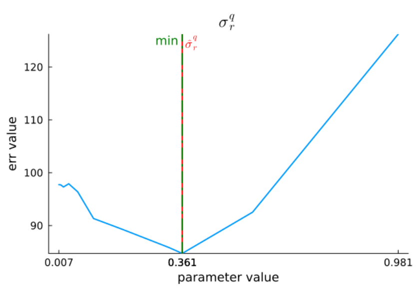
(d) $\gamma_{pa}^{race=black}$



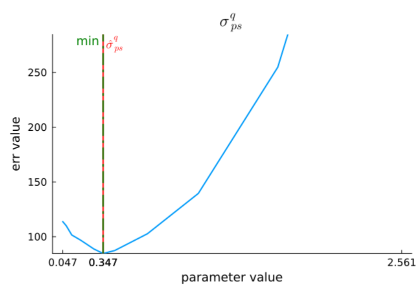
(e) $\gamma_{pa}^{race=other}$



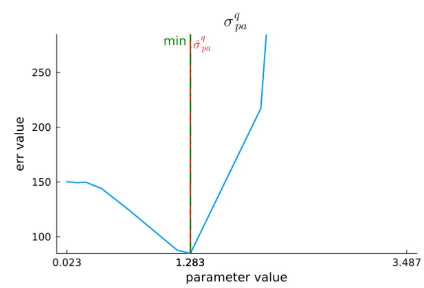
(f) γ_{hs}



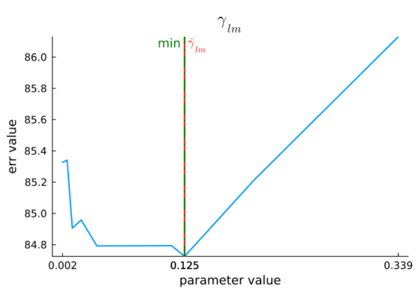
(g) σ_r^q



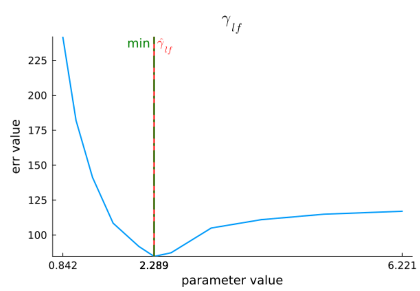
(h) σ_{ps}^q



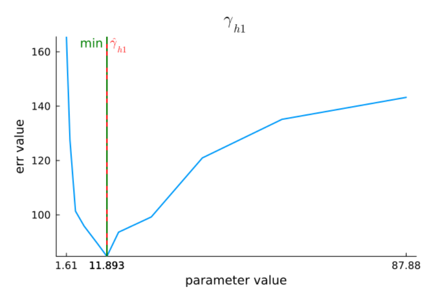
(i) σ_{pa}^q



(j) γ_{lm}

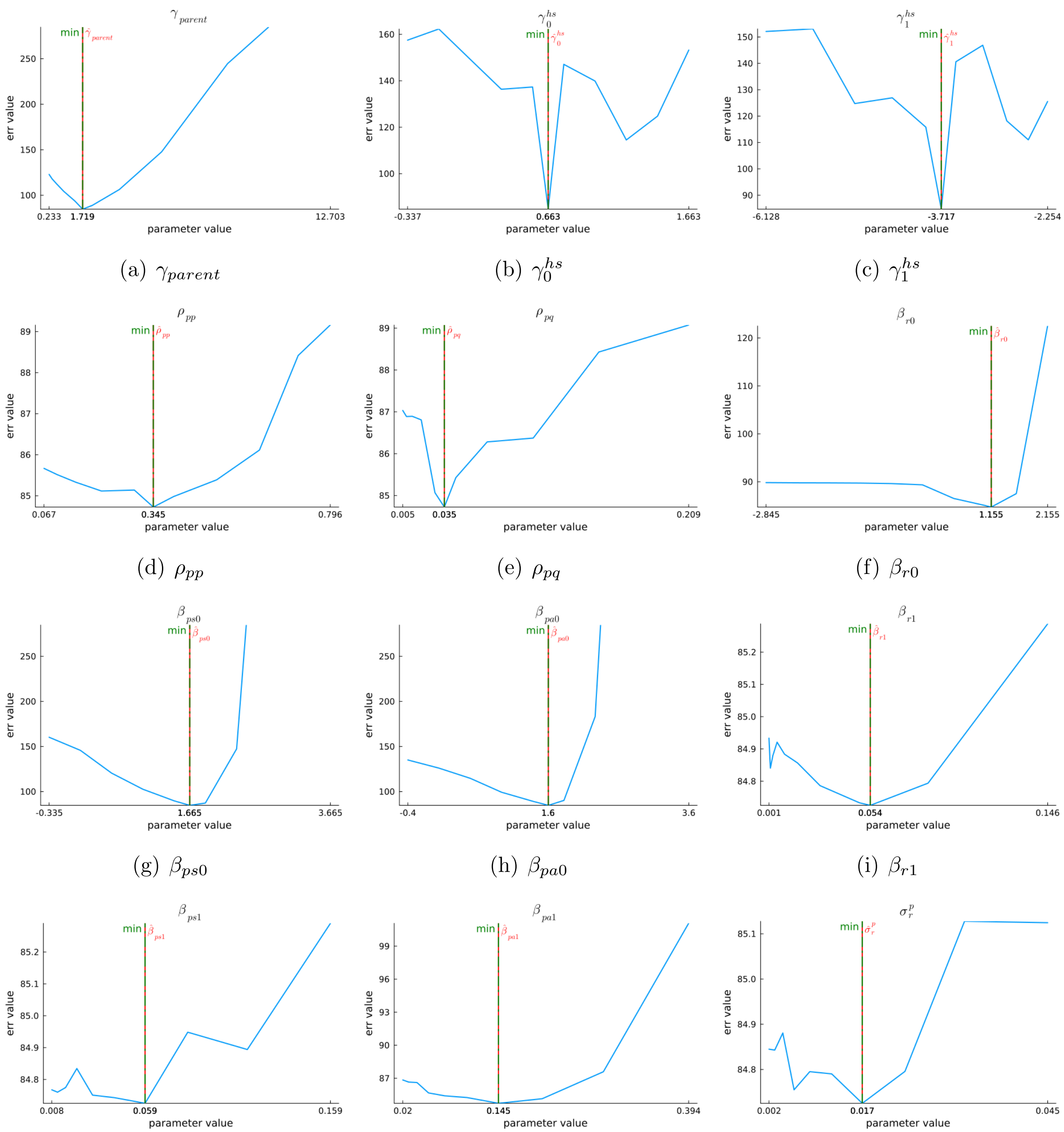


(k) γ_{lf}



(l) γ_{h1}

Figure 13: Identification graphs



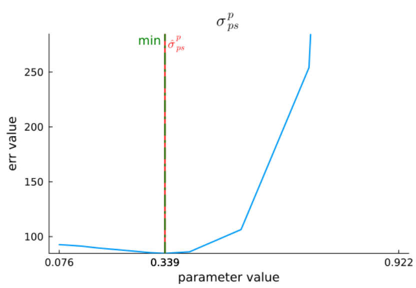
(a) γ_{parent} (b) γ_0^{hs} (c) γ_1^{hs}

(d) ρ_{pp} (e) ρ_{pq} (f) β_{r0}

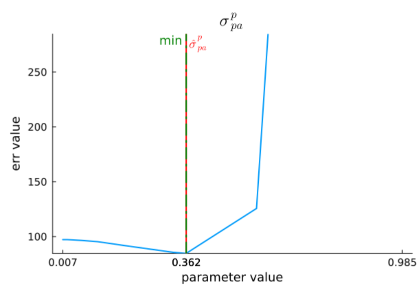
(g) β_{ps0} (h) β_{pa0} (i) β_{r1}

(j) β_{ps1} (k) β_{pa1} (l) σ_r^p

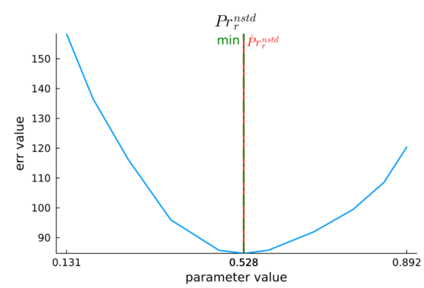
Figure 14: Identification graphs



(a) σ^p_{ps}



(b) σ^p_{pa}



(c) Pr^{nstd}_r

G Additional Counterfactual Tables

Table 26 presents how different hypothetical policies that change the rules of Child Care Development Fund (CCDF) funded subsidies could reduce the gap in maternal work arrangements, formal care usage, and skill development between lower SES households and higher SES households.

Table 26: How this closes the gap between lower SES and higher SES households

	Baseline			Gap close by what (%) percentage under different counterfactual situations		
	Mother with no college education	Mother with bachelor + degree	Gap between no collge v.s. bachelor +	No rate ceiling rc	No copayment $\psi = 0$	Accessible to all eligible hh $\pi_s = 1$
				(1)	(2)	(3)
Maternal Work Arrangement						
$\mathbf{I}$(work)	0.46	0.67	0.21	-0.25	-0.25	-0.80
total work hours	14.55	24.55	10.00	-0.10	0.30	-4.28
Care Arrangement						
$\mathbf{I}$(use provider care)	0.24	0.46	0.22	-0.29	-1.15	-3.98
total provider hours	9.84	22.13	12.29	-0.14	-0.01	3.67
Skill Development						
$\ln h_1$	-0.29	0.24	0.53	0.00	0.01	1.85

Table 27 and Table 28 show how different counterfactual policies providing direct price subsidies to households in need could influence households' decisions and reduce the gaps between lower SES and higher SES households.

H Representativeness of the NSECE Data

H.1 Comparing the NSECE with the ATUS Data

Using the American Time Use Survey (ATUS) data, this section aims to demonstrate how representative the NSECE data is. In the ATUS 2017-2018 data, two scheduling related questions are used for this comparison. The advantage of these two questions in ATUS is it asked about a 'usual' week instead of the '*past week*', which can rule out sudden scheduling shock.

One question asked 'Type of schedule usually worked', the answers can be: 1)Daytime-most work done between 6 a.m. and 6 p.m.; 2)Evening shift-most work done between 2 p.m. and 12 a.m.; 3)Night shift-most work done between 9 p.m. and 8 a.m.; 4)Rotating shift-hours change periodically; 5)Split shift-two distinct periods each day; 6)Irregular schedule; 7)Some other shift. Another type of questions are indicators, which asked 'Usually worked

Table 27: Counterfactual simulation of impacts of other potential schedule related subsidies

	Baseline	**(%) percentage change** under different counterfactual situations			
	Mother with no college education	provider price subsidy to any STD*hrs used	provider price subsidy to any NSTD*hrs used	provider price subsidy to any STD hrs used cond. $< \bar{y}^{**}$	provider price subsidy to any NSTD hrs used cond. $< \bar{y}^{**}$
		(1)	(2)	(3)	(4)
Maternal Work Arrangement					
I(work)	0.46	1.19	1.49	0.07	0.07
total work hours	14.55	1.95	0.93	0.23	-0.07
frac of nonstandard hrs	0.33	-7.75	6.14	-1.47	1.05
Care Arrangement					
I(use provider care)	0.24	8.67	5.05	0.42	0.70
total provider hours	9.84	9.72	3.44	1.46	1.01
frac of nonstandard hrs	0.21	-31.73	31.50	-2.78	7.20
Skill Development					
$\ln h_1$	-0.29	↑ 0.22	↑ 0.15	↑ 0.05	↑ 0.01
($/week) hh inc bef subsidy	1148.62	1151.88	1150.82	1148.90	1148.54
provider cost bef subsidy	46.58	52.21	48.09	47.33	46.95
provider cost after subsidy	36.18	12.63	28.03	33.91	35.59

* STD denotes "standard" and NSTD denotes "nonstandard".

** $\bar{y}$ is the federal poverty level.

Table 28: Gaps close by what percent under direct schedule subsidies

	Baseline			**Gap close by what (%) percentage** under different counterfactual situations			
	Mother with no college education	Mother with bachelor + degree	Gap between no collge v.s. bachelor +	provide price subsidy to any STD*hrs used	provide price subsidy to any NSTD hrs used	provider price subsidy to any STD hrs used cond. $< \bar{y}$	provider price subsidy to any NSTD hrs used cond. $< \bar{y}$
				(1)	(2)	(3)	(4)
Maternal Work Arrangement							
I(work)	0.46	0.67	0.21	-2.63	-3.28	-0.16	-0.16
total work hours	14.55	24.55	10.00	-2.84	-1.35	-0.34	0.10
Care Arrangement							
I(use provider care)	0.24	0.46	0.22	-9.43	-5.49	-0.46	-0.76
total provider hours	9.84	22.13	12.29	-7.78	-2.76	-1.17	-0.81
Skill Development							
$\ln h_1$	-0.29	0.24	0.53	-0.12	-0.08	-0.03	0.00

Table 29: Counterfactual simulation of impacts of lump-sum subsidies

	Baseline	(%) **percentage change** under different counterfactual situations		
	no college	lump sum subsidy (1)	lump sum subsidy cond. on hhinc< $\bar{y}$ (2)	lump sum subsidy cond. on hhinc< $\bar{y}$ * and lfp of mom>0 (3)
Maternal Work Arrangement				
I(work)	0.46	-24.00	-21.68	0.60
total work hours	14.55	-17.52	-16.37	-2.03
frac of nonstandard hrs	0.33	-2.10	-1.03	-2.50
Care Arrangement				
I(use provider care)	0.24	-24.25	-23.99	1.16
total provider hours	9.84	-11.29	-12.35	-1.04
frac of nonstandard hrs	0.21	9.29	10.84	-3.76
Skill Development				
$\ln h_1$	-0.29	↑ 6.69	↑ 6.65	↓ 0.09
($/week) hh inc bef subsidy	1148.62	1107.57	1112.43	1142.61
provider cost bef subsidy	46.58	41.32	40.20	46.04
provider cost after subsidy	36.18	34.50	33.80	35.42

* $\bar{y}$ is the federal poverty level.

on Mon/ Tue/ $\cdots$ / Sat/ Sun'.

Though weekends are commonly counted as nonstandard work hours in the literature and in this paper, for comparison between NSECE and ATUS, it is hard to define what 'usually worked on Sat/Sun' means using the NSECE calendar data. Therefore, for this specific comparison I define nonstandard schedule as 'most work is done outside of 6 a.m. and 6 p.m.'. The following table only includes working mothers ages between 18 and 50 (or working fathers ages above 18) whose youngest child ages between zero and four.

After excluding those who reported 'last week's work schedule is unusual' in the NSECE data, Table 30 presents that conditional on working more than 10 hours, the NSECE data is quite consistent with the ATUS data.

H.2 Comparing the NSECE with the CPS, NLSY97, ATUS Data

NSECE 2019

The NSECE contains detailed calendar information: a calendar week is comprised of 672 slots of 15-minute duration. I define standard hours as from 8 a.m.-6 p.m. Monday through Friday. Any hour outside of this range is defined as nonstandard hours.

CPS Supplements: Work Schedules (1985 1991 1997 2001 2004) data

The CPS work supplements data includes information about the number of days worked in a usual week for the primary job; and the time of day at which the respondent's primary

Table 30: Comparing the NSECE(2019) data with the ATUS(2017-18) data

	(%)in each category		(%)work nonstandard schedule		average hours worked	
Working mothers						
conditional on	ATUS	NSECE	ATUS	NSECE	ATUS	NSECE
hours>0	100	100	0.152	0.200	37.84	32.29
hours>10	0.980	0.896	0.146	0.142	38.79	36.00
hours>15	0.962	0.856	0.141	0.126	39.50	37.25
hours>30	0.864	0.659	0.125	0.066	42.42	42.63
Working fathers						
	(%)in each category		(%)work nonstandard schedule		average hours worked	
conditional on	ATUS	NSECE	ATUS	NSECE	ATUS	NSECE
hours>0	100	100	0.176	0.143	42.34	44.88
hours>10	0.986	0.974	0.175	0.122	43.06	46.31
hours>15	0.976	0.965	0.172	0.116	43.49	46.74
hours>30	0.925	0.891	0.160	0.067	45.04	49.27

Source: American Time Use Survey Leave Module 2017-18; National Survey of Early Care and Education 2019.

Notes: This tabulation is based on the mother aged between 18-50, works, and has a child ages between 0-4. Those who reported 'last week's work schedule is unusual' in the NSECE data are excluded.

job usually started/ended last week. Standard hours are defined as from 8 a.m.-6 p.m. if worked ≤ 5 days in this data set, and the rest of the hours are defined as nonstandard hours.

ATUS 2017-18

The schedule-related question is asked as follows. Type of schedule usually worked: 1)Daytime-most work done between 6 a.m. and 6 p.m. 2) Evening shift-most work done between 2 p.m. and 12 a.m. 3) Night shift-most work done between 9 p.m. and 8 a.m. 4) Rotating shift-hours change periodically. 5) Split shift-two distinct periods each day $\cdots$ For the ATUS data, I define the nonstandard fraction as 0 if most work is done between 6 a.m. and 6 p.m. and 1 otherwise.

NLSY97 round 1-19

The NLSY97 survey asked the respondent "Which of the following categories best describes the type of schedule you (work/worked) for this employer (at this time/that time when you left)?". The answer could be 1) Regular day shift; 2) Regular evening shift; 3) Regular night shift; 4) Shift rotates; 5) Split shift; 6) Irregular schedule or hours; 7) weekends. If the respondent reports he/she works a "regular day shift", the nonstandard fraction of work hours is defined as 0; if the respondent reports "shift rotates" or "split shift", the nonstandard fraction of work hours is defined as 0.5; for all the other cases like "regular evening shift", "regular night shift", "irregular schedule or hours", and "weekends", the nonstandard fraction of work hours is defined as 1.

Table 31 shows that schedule information provided in different datasets is consistent. Even a rough schedule variable is good enough to reflect similar information as is reflected by precise calendar variables.

H.3 Concerns for Seasonality

About three-quarters of NSECE 2019 main interviews were completed in the first quarter of the year, and the rest of the main interviews were completed before August. To address concerns about work schedule seasonality, I use ATUS data and perform the following analysis. Table 32 and Table 33 show the proportion of people who work nonstandard schedules does not fluctuate significantly over the year using the first quarter as the base group. I further conduct the F-test for column (4) in Table 33 separately for the mother and the father, where the null hypothesis is as follows that all the parameters ahead of indicators for season are the same. The results are consistent, and none of the null hypothesis can be rejected, meaning that nonstandard schedule seasonality is not significant.

$$H_0 : \beta_{1st\ qtr} = \beta_{2nd\ qtr} = \beta_{3rd\ qtr} = \beta_{4th\ qtr} \tag{40}$$

$$p - value(mom) = 0.5468; \quad p - value(dad) = 0.9577 \tag{41}$$

Table 31: Work schedule arrangement

	Average fraction of nonstandard work hours (or fraction of people work nonstandard schedules)							
	NSECE (detailed schedule)		CPS (detailed schedule)		ATUS(17-18) (rough schedule)		NLSY97 (rough schedule)	
	male	female	male	female	male	female	male	female
no college			0.185	0.117	0.237	0.223	0.297	0.310
some college			0.164	0.093	0.225	0.170	0.295	0.265
bachelor+			0.077	0.056	0.100	0.077	0.177	0.141
With young child ages under 5								
	male	female	male	female	male	female	male	female
no college	0.181	0.111	0.191	0.124	0.222	0.351	0.280	0.298
some college	0.159	0.077	0.169	0.084	0.210	0.086	0.286	0.227
bachelor+	0.107	0.068	0.083	0.048	0.029	0.003	0.151	0.102

Source: National Survey of Early Care and Education 2019; Current Population Survey (1985 1989 1991 1997 2001 2004); National Longitudinal Survey of Youth 1997; American Time Use Survey Leave Module 2017-18.

Notes: This tabulation is based on the respondents aged between 18-40; who are not self-employed or in the military; and who work more than 35 hours per week.

For this specific analysis and using the ATUS survey question, I define nonstandard schedule as 'most work is done outside of 6 a.m. and 6 p.m.' or 'usually works on Saturday/Sunday'. The tabulation for mother (or for father) is based on the mother (or the father) ages between 18-50, works, and has child ages between 0-4.

Table 32: Fraction of mothers (or fathers) who work nonstandard schedules

Fraction of mothers work nonstandard schedules					**Distribution of the interview**				
	education					education			
season	no coll	some coll	bachelor+	Total	season	no coll	some coll	bachelor+	Total
1	0.630	0.317	0.090	0.277	1	31.47	19.43	29.86	26.47
2	0.534	0.316	0.055	0.253	2	17.76	28.33	21.60	22.91
3	0.512	0.380	0.004	0.288	3	26.07	28.37	24.46	26.43
4	0.558	0.310	0.042	0.266	4	24.70	23.86	24.08	24.19
Total	0.564	0.333	0.050	0.272	Total	100	100	100	100
					Total	31.39	37.39	31.23	100
Fraction of fathers work nonstandard schedules					**Distribution of the interview**				
	education					education			
season	no coll	some coll	bachelor+	Total	season	no coll	some coll	bachelor+	Total
1	0.339	0.348	0.143	0.239	1	26.38	23.31	26.01	25.39
2	0.487	0.430	0.161	0.338	2	28.76	25.35	23.72	26.52
3	0.429	0.436	0.147	0.292	3	23.45	28.17	25.89	25.43
4	0.340	0.450	0.111	0.259	4	21.41	23.18	24.37	22.66
Total	0.403	0.417	0.141	0.282	Total	100	100	100	100
					Total	46.05	29.22	24.72	100

Source: American Time Use Survey Leave Module 2017-18.

Notes: The tabulation for mother (or for father) is based on the mother (or the father) ages between 18-50, works, and has child ages between 0-4.

Table 33: Regression of nonstandard schedule on season.

Dependent Variable:	I(the mother works nonstandard schedule)*				I(the father works nonstandard schedule)*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
2nd quarter	-0.024	0.008	0.020	0.046	0.099	0.089	0.088	0.015
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)
3rd quarter	0.011	0.015	0.025	-0.012	0.053	0.046	0.049	0.023
	(0.10)	(0.07)	(0.06)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)
4th quarter	-0.011	-0.005	0.020	0.007	0.020	0.025	0.020	0.008
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Age		-0.011*	-0.010*	-0.008		-0.004	-0.002	-0.004
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Own child under 1 in hh			-0.127**	-0.083			0.022	-0.038
			(0.05)	(0.06)			(0.05)	(0.04)
Own child age 1 to 2 in hh			-0.057	-0.076			0.010	-0.080
			(0.04)	(0.05)			(0.05)	(0.04)
Own child age 3 to 5 in hh			-0.028	-0.030			-0.038	-0.085
			(0.04)	(0.04)			(0.05)	(0.05)
education		Y	Y	Y		Y	Y	Y
race		Y	Y	Y		Y	Y	Y
marital status			Y	Y			Y	Y
state fixed effect				Y				Y
occupation fixed effect				Y				Y
constant	0.277***	0.621***	0.655***	0.583***	0.239***	0.389**	0.334*	0.513***
	(0.05)	(0.14)	(0.15)	(0.16)	(0.04)	(0.13)	(0.15)	(0.12)
R-sqr	0.001	0.263	0.292	0.567	0.007	0.153	0.168	0.581
Obs	768	766	766	687	843	841	840	733

Source: American Time Use Survey Leave Module 2017-18.

Regression is clustered by occupation.

* In this tabulation, nonstandard schedule is defined as most work done outside of 6 a.m. and 6 p.m. or usually works on Saturday or Sunday

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