

# Heterogeneous Father Time Spent and Inequality of Child Development in Health and Cognition <sup>\*</sup>

Jiaqi Li  
University of Warwick <sup>†</sup>

Yaolang Zhong  
University of Warwick <sup>‡</sup>

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## Abstract

The literature on child development has a strong focus on maternal time use, female labour supply and child outcomes. This paper first highlights that fathers with higher labour supply also spend significantly more time at home with their children, while unemployed fathers spend the least time with their children. The positive association between labour supply and parenting time exists only for fathers, but not for mothers. To quantify the contribution of the heterogeneity in fathers' time investment to the inequality in child development, this paper estimates production functions for cognitive and health development for children aged 1-18 with the father's time input and the mother's time input using the PSID time diary. The estimation is based on a nonlinear latent factor model with local gender-specific labour demand shocks as instruments with a control function approach. Counterfactual analysis to remove father heterogeneity in time investment reduces 22 per cent of the variance in child cognition and 49 per cent of the variance in child health explained by the model among children aged 12-18.

**Keywords:** Paternal Time Allocation, Child Development, Inequality, Nonlinear Factor Models, Human Capital Production Functions

**JEL:** D13, J13, J21, J22, J24, I14

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<sup>†</sup>Department of Economics, University of Warwick . Email: [j.li.51@warwick.ac.uk](mailto:j.li.51@warwick.ac.uk)

<sup>‡</sup>Department of Economics, University of Warwick. Email: [yaolang.zhong@warwick.ac.uk](mailto:yaolang.zhong@warwick.ac.uk)

# 1 Introduction

Soon after birth, children from poorer backgrounds fall behind in every aspect of human capital development. Consequently, they are likely to be poor as adults with low wages and earnings. Such "intergenerational income persistence" is often interpreted as an indicator of lacking equal opportunities (Chetty et al., 2014; Blanden, 2019).

Parental investment is crucial for child development. Extensive research studies the relationship between maternal parenting time, female labour supply and child development. Mothers face a trade-off to allocating time between parenting and work. Working more hours may increase consumption and expenditures on goods for the child, but it is at the expense of her time spent with the child. Therefore, some studies conclude that the net effect of maternal labour supply may be negative on child development (Baum II, 2003; Ruhm, 2004; Bernal, 2008; Agostinelli, 2021).

However, surprisingly, little has been written on the role of fathers in child development. Does the assumption in the trade-off of time between work and parenting hold for fathers? Is there any significant heterogeneity in time investment among fathers? If so, does the heterogeneity contribute to the inequality of child development, such as health and cognition?

Not just in academic research, the paternal role in fostering child development seems largely absent in policy debates. This may reflect the public perception and even the consent of fathers' absence of childrearing. For example, Bernal (2008) excludes fathers in the modelling and estimating of the development of child cognition, by assuming that fathers have no active role in the child development process. However, seminal work by Del Boca et al. (2014) demonstrates that both parents' time inputs are equally important for their children's cognitive development. By contrast, the authors find money expenditures much less productive in fostering child development.

First of all, we document new stylised facts about fathers' time investment using a PSID time diary. We first highlight substantial heterogeneity in the father's time spent with the child, as shown in Figure 1 and 2. Furthermore, there is a strong positive association between family income and the father's time investment. Children in families with higher total incomes receive substantially more time input from their fathers on a daily basis both on weekends or weekdays, either actively (participated in the activities) or passively (present during the activities). And this association holds regardless of race, age or the sex of the child, as shown in Appendix A.

Furthermore, the pattern is not driven by families with higher incomes having a larger budget set to allow fathers to increase parenting and reduce hours worked. Instead, as shown in Figure 3, fathers working more hours in the labour market tend to spend more time with their child. Conversely, unemployed fathers tend to spend the least amount of

Figure 1. Family income and weekend parenting hours

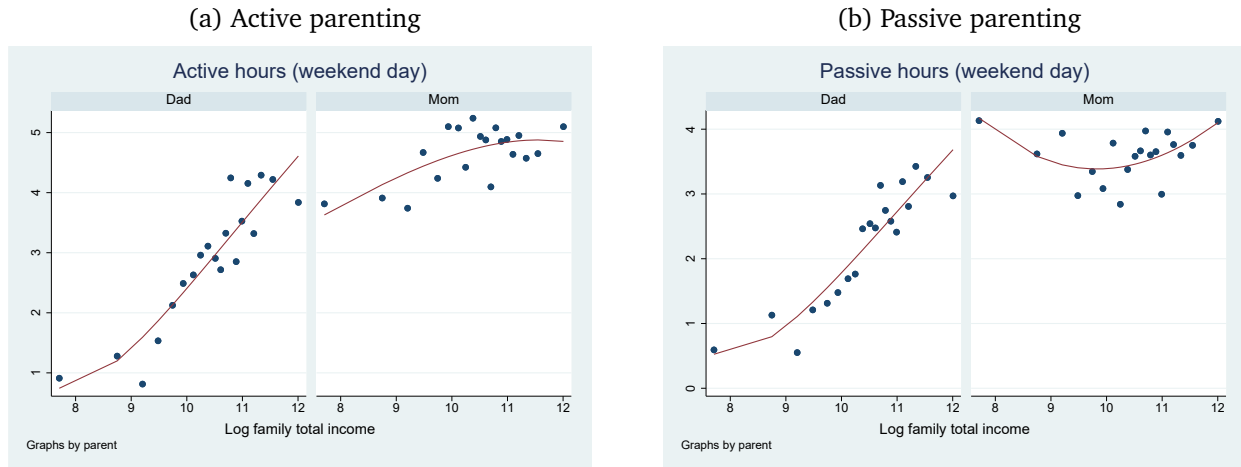


Figure 2. Family income and weekday parenting hours

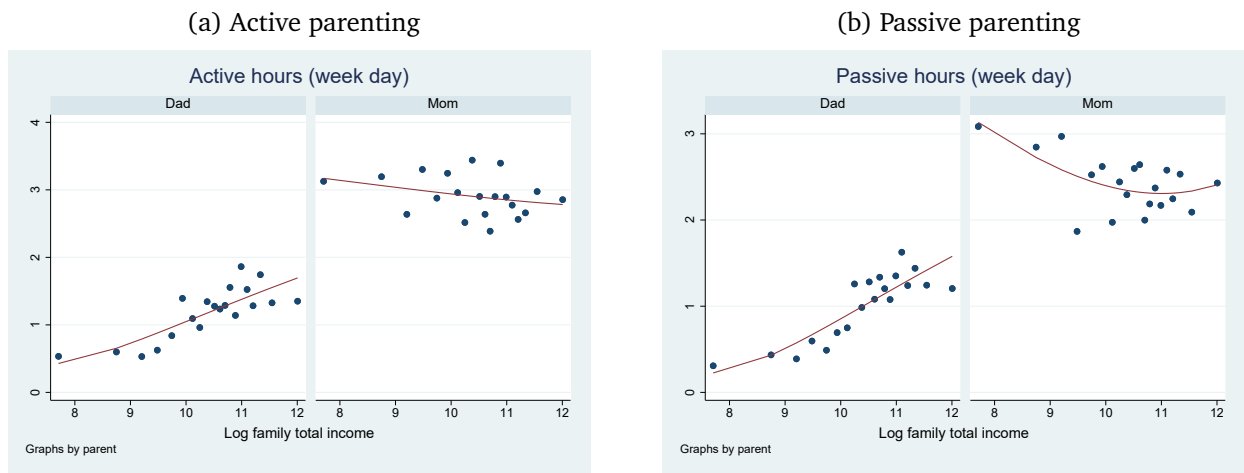
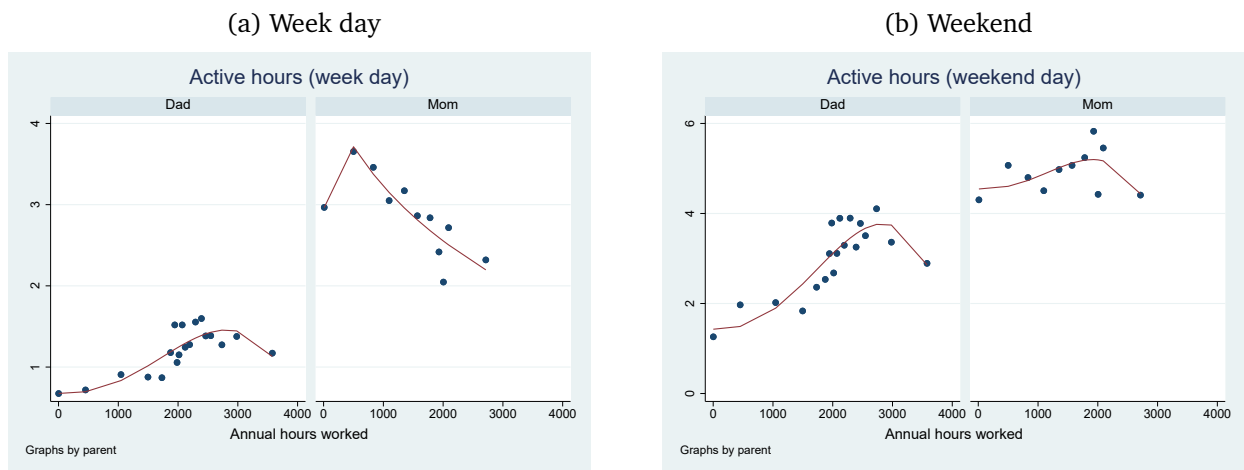


Figure 3. Labor supply and parenting hours



Notes: Active parenting includes activities in which a parent participated. Passive parenting includes activities where a parent was present. Author's calculation using PSID CDS 24-hour Time Diary 1997.

time with their child than the rest of the fathers. This indicates that the trade-off for parents in their time allocation between parenting and work, a common assumption of the child development literature, does not apply to fathers.

Therefore, this paper quantifies how much child development inequality (both cognition and health) is explained by the heterogeneity of fathers' time investment. In the absence of policy-induced changes in fathers' time input, a counterfactual simulation exercise is useful to demonstrate how intervention in fathers' time investment could reduce child development inequality. This requires a good understanding and reliable estimates of the role of fathers' time in the dynamic structure of child development. When parental investments are treated as endogenous, identification requires instruments that are relevant and can be excluded from the production function.

Therefore, we estimate a nonlinear latent factor model of child development production function and use a control function approach with local gender-specific labor demand shocks to instrument for endogenous mothers' time input and fathers' time input respectively. The identification assumption is that after controlling for family income, local gender-specific labour demand shock is uncorrelated with unobservable in the child development production function. Similar to [Agostinelli \(2021\)](#), the idea follows [Attanasio et al. \(2020\)](#), using local prices for food, clothing, notebooks and medication for worms, and [Attanasio \(2015\)](#), using the price of toys and food in the municipality of residence, to account for the endogeneity of parental monetary investment.

We perform counterfactual analyses by setting the father's time spent equally among all children. As the result, we find that the variation in child cognition in the last stage (between ages 12 to age 18) is reduced by 22 percent. Furthermore, the variation in child health is reduced by 49 percent.

This paper first contributes to the intergenerational mobility literature ([Chetty et al., 2014](#); [Blanden, 2019](#)), by providing a new mechanism of heterogeneous fathers' time input for intergenerational persistence. Second, this paper contributes to the early child development literature ([Cunha and Heckman, 2007](#); [Cunha et al., 2010, 2013](#); [Del Boca et al., 2014](#); [Agostinelli, 2021](#); [Attanasio, 2015](#); [Attanasio et al., 2020](#)) by highlighting the role of fathers in explaining the inequality of child cognition and health.

Given the substantial heterogeneity in fathers' parenting inputs, this paper demonstrates that policies effectively increasing fathers' engagement with their children, shall have significant effects in reducing child inequality and lack of intergenerational mobility, especially among children from low-income families whose fathers appear to work the least and parent the least.

The rest of the paper is structured as follows. Section 2 documents the data and variables. Section 3 explains the production function, instrumental variables, control function, nonlinear factor model, and estimation. Section 4 presents the parameter estimates and

conducts counterfactual analysis by equalizing the fathers' time spent among all children. Section 5 concludes.

## 2 Data

In estimation, We make use of the PSID Child Development Supplement (CDS) with information about children in PSID families. PSID-CDS collects comprehensive measures from child development and parenting. CDS collects measures in 1997, 2001, 2007, 2013, and 2019.

Our full data set is an unbalanced panel of 5463 children. 2194 children have both 1997 and 2001 measurement collected. Among them, 1086 children are observed in all three years in 1997, 2001 and 2007 and 1107.

By the year 2014, all children included in the original CDS in 1997 had aged into adulthood. A new round of CDS data collection in that year included all eligible children aged 0-17 years living in PSID families in 2013.

Table 1. Child, households and parenting hours

	Mean	SD
Maternal year of schooling	7.73	5.29
Paternal year of schooling	12.94	2.30
Annual total family income (2015 price)	8260.03	7792.47
Annual child care expenditure (2015 price)	163.31	383.45
Girls	0.49	0.50
White	0.50	0.50
Age	6.01	3.66
mother active hours on a weekend	4.61	3.34
father active hours on a weekend	2.73	3.19
mother passive hours on a weekend	3.54	2.88
father passive hours on a weekend	2.04	2.58
mother active hours on a weekday	2.90	2.55
father active hours on a weekday	1.11	1.61
mother passive hours on a weekday	2.43	2.26
father passive hours on a weekday	0.95	1.47

Note: Based on PSID-CDS data in 1997. Monetary measured deflated by CPI index. Parenting is active when a parent participated and passive when the parent was only present in the house. Family total income consists of father and mothers' labor income and household non-labor income or debt.

As shown in Table 1, mothers spend more time in parenting compared to fathers in any kind of measures by passive or active involvement or by weekend or week day measures. Family income and childcare expenditure are deflated by CPI index.

## 2.1 Child mental and physical health

Child mental health is measured by the child depression inventory in PSID. It measures child mental health in the dimensions of appearance, crying, doing things okay, friends, irritability, isolation, love, sadness, self-hate, and things will work out. Child physical health is measured by height, weight status, and calculated Body Mass Index adjusted for the child's age and gender.

## 2.2 Cognition

First, child cognition is assessed by Woodcock-Johnson tests in several dimensions, including abilities in applied problems, broad math, broad reading, calculation, letter-word, and passage comprehension. Second, for children over 7, the additional measure is available. The Memory for Digit Span assessment, a component of the Wechsler Intelligence Scales for Children-Revised (WISC-R), is a measure of short-term memory (Wechsler, 1974)

## 2.3 Parenting

Parent-child interaction measures include indicators if parents build something with the child; clean the house with the child; discuss books with the child; discuss family with the child; do crafts with the child; do dishes with the child; do yard work with the child; go to the store with child; play games with child; play sports with child; prepare food with child; use the computer with child; wash clothes with child.

Parental warmth measures include indicators if parents discuss TV programs with their child (6 years and above), expressed appreciation, have favourite activity with the child; had parenting classes before birth; played together; said I love you; show physical affection; talked about current events; talked about interests; talked about relationships; talked about their day.

## 2.4 Parental time investment

Parental time investment is calculated by the accurate time diary in PSID. 24-hour time diaries describing their activities on one randomly selected weekday and one randomly selected weekend day. Child diary records all activities of the child throughout the entire day, including begin time, end time, activity type, location, and social contact engaged in the activities. Parental involvement is further distinguished by passive and active involvement. Each child has the diary measured both on a weekday and a weekend day.

## 2.5 Family environment

Two domains measure family environment. First is the set of measures of family conflict, such as the calmness of family discussion, frequencies of family fights, frequencies of family hit, the frequencies of family throw things. Second domain is cognitive simulation of home scale. This include the number of books read past year, the number of books in the house, and the number of cellphones in the house. Third domain is home and neighborhood including the noise inside the house, noise outside the house, and the cleanliness of the house.

## 2.6 Instruments for endogeneity of parental time investment

We propose to use local gender-specific labor demand as an instrument for time spent with children. It is calculated using IPUMS CPS which harmonizes microdata from the monthly U.S. labor force survey, the Current Population Survey (CPS), covering the period 1962 to the present. We measure this as the residual from a regression of employment rate on a linear year trend, separately by race, state, and gender. We assume that the deviation from linear prediction reflects local labor race-gender-state specific demand shock, and does not affect child production function after controlling for family income, acting as an exclusion restriction. Furthermore, the demand shocks are standardised to have mean 0 and standard deviation 1, separately by gender.

# 3 Model and estimation

## 3.1 Production function set up

The framework closely follows seminal work by [Cunha and Heckman \(2007\)](#), [Cunha et al. \(2010\)](#), and [Attanasio et al. \(2020\)](#). By assuming that human capital has two relevant dimensions, cognition and health.

$$H_a = H(\theta_a^c, \theta_a^h) \quad (1)$$

We follow [Cunha et al. \(2010\)](#) and [Attanasio et al. \(2020\)](#) to express the evolution of cognition and health by a series of dynamic production functions over stages ( $t$ ) of childhood. We material parental investment for simplicity as [Del Boca et al. \(2014\)](#) find that money inputs are not productive compared to both parents' time input using the same PSID dataset.

$$\begin{aligned}\theta_{c,t+1} &= G(\theta_{ct}, \theta_{ht}, \theta_{mt}, \theta_{dt}, X_t) \\ \theta_{h,t+1} &= F(\theta_{ct}, \theta_{ht}, \theta_{mt}, \theta_{dt}, X_t)\end{aligned}\tag{2}$$

Both child cognition and health in the period depend on the cognition, health, maternal time investment, and paternal time investment during the period, also family income and individual characteristics including race and gender. The production functions define how cognition, health, and parental investment interact in the dynamic structure. We group the child development period by 3 stages including 0 to 5, 6 to 11, and 12 to 18. we denote child's stage by  $t$ . Following [Cunha et al. \(2010\)](#), we assume a CES function. Therefore, we have that

$$\begin{aligned}\theta_{c,t+1} &= [\delta_{ct}(\theta_{ct})^{\rho_t} + \delta_{ht}(\theta_{ht})^{\rho_t} + \delta_{mt}(\theta_{mt})^{\rho_t} + \delta_{dt}(\theta_{dt})^{\rho_t}]^{\frac{1}{\rho_t}} A_{ct} \\ \theta_{h,t+1} &= [\alpha_{ct}(\theta_{ct})^{\zeta_t} + \alpha_{ht}(\theta_{ht})^{\zeta_t} + \alpha_{mt}(\theta_{mt})^{\zeta_t} + \alpha_{dt}(\theta_{dt})^{\zeta_t}]^{\frac{1}{\zeta_t}} A_{ht}\end{aligned}\tag{3}$$

The parameters of the production function all vary with age  $t$ . The parameters  $\rho_t$  and  $\zeta_t$  determine the elasticity of substitution between the various inputs in the cognition and noncognition production function, respectively. The  $\alpha_t$ s and the  $\delta_t$ s sum to one, respectively, within each period and where

$$\begin{aligned}A_{ct} &= \exp(d_{0t} + d'_{X_t}X_t + u_{ct}) \\ A_{ht} &= \exp(g_{0t} + g'_{X_t}X_t + u_{ht})\end{aligned}\tag{4}$$

Characteristics  $X_t$  include time-varying family income as well as the race and gender of the child.

### 3.2 Time investment

In a utility maximisation of parental choices such as [Del Boca et al. \(2014\)](#), the assumption is that parents have perfect information on the child production function, which is against evidence such as [Cunha et al. \(2013\)](#). Therefore, we follow [Attanasio et al. \(2020\)](#) to estimate a reduced form investment equation that includes parental education, race, gender of the child, current period cognition and non-cognition of the child, to allow for feedback effect. However, the endogeneity problem arise as unobservable reasons may drive both parental investments and correlate with shocks in the child quality production functions.

### 3.3 Control for the endogeneity of time investment

Identification requires instruments that are relevant for parental investment but are excluded from the child quality production function. As explained in section 2, we use residuals from the deviation from linear trend in gender-, race-, and state-specific linear trend in employment as a proxy for local labor demand shocks.

$$\begin{aligned}\ln \theta_{mt} &= \gamma_0 + \gamma_{ct} \ln \theta_{ct} + \gamma_{ht} \ln \theta_{ht} + \gamma'_{Xt} X_t + \gamma'_{pt} \ln p_{mt} + v_t \\ \ln \theta_{dt} &= \eta_0 + \eta_{ct} \ln \theta_{ct} + \eta_{ht} \ln \theta_{ht} + \eta'_{Xt} X_t + \eta'_{pt} \ln p_{dt} + v_t\end{aligned}\tag{5}$$

With the instruments, we use a control function approach, similar to Attanasio et al. (2020 b). Specifically, assume that

$$\begin{aligned}E(u_{ct} | Q_t, Z_t) &= \kappa_c v_t \\ E(u_{ht} | Q_t, Z_t) &= \kappa_h v_t\end{aligned}\tag{6}$$

Where  $Q_t$  is the full set of variables in the production functions including parental investments, and  $Z_t$  is the instruments. The control function procedure is to include the estimated residual from the time investment equation as regressors. Assuming that parental time investments are exogenous amounts to impose. These are testable hypotheses to check empirically. The identification assumption is that variation in local female and male labour demand is uncorrelated to omitted inputs in the child quality production function after controlling for family total income.

### 3.4 Latent factor models and the measurement system

Child cognition, child health, and both mother's and father's time investment are inherently latent [Cunha et al. \(2010\)](#). Directing using proxies without correcting for measurement error would lead to biases with unknown directions because of the nonlinearity of the production function.

We start by assuming a semi-log relationship between the measurements and latent variables:

$$m_{jkt} = a_{jkt} + \lambda_{jkt} \ln(\theta_{kt}) + \epsilon_{jkt}\tag{7}$$

In a matrix form:

$$M = \mathbf{A} + \mathbf{\Lambda} \ln \theta + \Sigma \epsilon\tag{8}$$

Here  $m_{jkt}$  denotes the  $j$ th measurements related to the  $k$ th latent variable in time  $t$ , and  $\lambda_{jkt}$  is the corresponding factor loading accompanied with the measurement error  $\epsilon_{jkt}$ .

The joint distribution of the log latent factors is assumed to be a mixture of Gaussian.

The departure from normality is necessary [Attanasio et al. \(2020\)](#) as assuming normality would restrict the production functions to be Cobb-Douglas (linear in logs) with the substitution elasticity equal to 1. For computational simplicity we assume there are only two underlying clusters, though generalizing to the case of more clusters is straightforward.

$$F_\theta = \tau\Phi(\mu_A, \Omega_A) + (1 - \tau)\Phi(\mu_B, \Omega_B) \quad (9)$$

where  $\tau$  is the mixture weights, namely the probability that each realised observation is from the first normal distribution.

The factor that all  $\theta$  are unobservable and the assumed above semi-log relationship between measurements and latent variables give rise to the mixture Gaussian distribution for the measurements system:

$$F_M = \tau\Phi(\Pi_A, \Psi_A) + (1 - \tau)\Phi(\Pi_B, \Psi_B) \quad (10)$$

where

$$\begin{aligned} \Psi_A &= \Lambda^T \Omega_A \Lambda + \Sigma; & \Psi_B &= \Lambda^T \Omega_B \Lambda + \Sigma \\ \Pi_A &= \mathbf{A} + \Lambda \mu_A; & \Pi_B &= \mathbf{A} + \Lambda \mu_B \end{aligned}$$

Finally, besides the latent variables in our model, there are also additional variables used in the production functions and as the instruments in the time investment functions. These variables are observable and we treat them as error-free measures so that they appear both in the measurement system and the latent variable system, which then means an augmented system of mixture Gaussian:

$$F_{\theta,X} = \tau\Phi(\mu_A^{\theta,X}, \Omega_A^{\theta,X}) + (1 - \tau)\Phi(\mu_B^{\theta,X}, \Omega_B^{\theta,X}) \quad (11)$$

Following [Cunha et al. \(2010\)](#) and [Attanasio et al. \(2020\)](#), the location and scale of the latent factors are set based on normalization restrictions. For child cognition, normalise the loading on Woodcock-Johnson letter-word test to one. Child health is normalised on the z scores of height. Father time inputs are normalised on active hours spent with the child on a weekday. Similarly, mother time inputs are normalised on active hours spent with the child on a weekday.

### 3.5 Estimation

Following to [Attanasio et al. \(2020\)](#), the estimation scheme consist of three steps:

(i) Use the expectation-maximization (EM) algorithm to estimate all the parameters that characterise the mixture Gaussian measurement system: the weights  $\tau$ , the mean vectors  $\Pi_A, \Pi_B$  and the covariance matrices  $\Psi_A, \Psi_B$ . While there is a closed-form solution

in both the E step and M step in each iteration thanks to the Gaussian assumption, the non-negligible amount of missing values due to the structure of the PSID dataset makes the calculations only conditional on the observed data of each observation. In each iteration, the temporarily obtained parameters should be taken carefully to prevent an ill-conditioned matrix in the next round.

(ii) Recover the parameters needed to characterize the joint distribution of latent variables  $\theta$ : the shift vector  $\mathbf{A}$ , factor loading matrix  $\Lambda$ , measurement error matrix  $\Sigma$ , the mean vectors  $\mu_A, \mu_B$  and the covariance matrices  $\Omega_A, \Omega_B$  from the parameters obtained in (i). Here four restrictions are imposed to reduce the degrees of freedom:

1. Assumption that the measurement error is mutually independent so that  $\Sigma$  is a diagonal matrix.

2. Assumption that each measurement links to only one underlying factor, so only the corresponding factor loading is non-zero. Besides, we impose normalisation following [Cunha et al. \(2010\)](#) and [Attanasio et al. \(2020\)](#). For child cognition, normalise the loading on Woodcock-Johnson letter-word test to one. Child health is normalised on the z scores of height. Father time inputs are normalised on active hours spent with the child on a weekday. Similarly, mother time inputs are normalised on active hours spent with the child on a weekday. In practice, we assign the above measurement as the first measurement for the associated factor.

3. The assumption that the growth of the measurement is due only to the growth of the associated latent variables. This, together with the normalisation of loading to the first measurement for each latent variable, imposes a restriction on the constant vector  $\mathbf{A}$  that the elements in  $A$  corresponding to each first measurement are unchanged dynamically, so we only need to pin down their values in the first period.

4. The normalisation that the weighted mean of the latent variables in the first period is zero:

$$\tau\mu_{A,t=0} + (1 - \tau)\mu_{B,t=0} = 0 \tag{12}$$

This helps us to identify elements in  $\mathbf{A}$  for all measurements in the first period, which are mathematically the empirical average of the measurements. Together with the restrictions above we can identify all the rest elements in  $\mathbf{A}$  as well as the loading  $\lambda$  and means  $\mu_A, \mu_B$ .

## 4 Results and counterfactual analysis

### 4.1 Estimates

We group the child development period into 3 stages including 0 to 5, 6 to 11, and 12 to 18. We report here some statistics characterizing the joint distribution of the latent variables. As shown in Table 2, the weight parameter  $\tau$  of the two mixtures is estimated to be 0.382 with its 95% confidence interval [0.36, 0.39]). This, together with most of the latent variables having distinct means across the two clusters (though the covariance matrix is not shown), suggests that the joint distribution of latent variables departs substantially from the multivariate normal distribution, and hence our implementation of mixture gaussian model is necessary and useful at least at capturing such departure.

Furthermore, as shown in Table 3, last period health is a very productive input for cognition at age 6. This suggests high complementarity between health and cognition during early childhood. Meanwhile, the complementarity in cognition across periods is only significant in later periods. Father's time spent appears to be very productive for child cognition between age 6 and 11, while the mother's time investment appears to be very productive for child cognition between age 12 to 18.

Column 5 and 6 in Table 3 presents the coefficients of control function residuals. The coefficients of the father's time investment residual become statistically significant for cognition and health at stage 3 (age 12 to 18). This suggests that father time investment is highly endogenous in adolescence such that paternal time spent is positively correlated with the unobservable in the production function of child development. Without a control function, the counterfactual analysis will yield an incomplete picture with biased estimates. The coefficients on the control function residual of fathers' time investment are significantly negative on health at age 6. This suggests that the father's time decision compensates child's health input, such that the father spends more time when the child is less healthy. The opposite is true for cognition at age 12. Father time investment positively responds to the level of child cognition at age 12.

Table 2. Mixture Weights and Means

	Mixture.A	Mixture.B
Weights	0.382 [0.36,0.39]	0.618 [0.61,0.64]
Mean Cognition Age 12	2.235 [2.17,2.266]	2.254 [2.236,2.32]
Mean Cognition Age 6	1.846 [1.816,1.871]	1.635 [1.617,1.652]
Mean Cognition Age 1	0.408 [0.352,0.436]	-0.251 [-0.269,-0.206]
Mean Health Age 12	2.153 [1.33,2.219]	2.265 [2.21,2.281]
Mean Health Age 6	1.697 [1.659,1.718]	1.377 [1.361,1.397]
Mean Health Age 1	-0.067 [-0.106,-0.042]	0.042 [0.025,0.065]
Mean Mom's Investment Age 12	1.603 [1.568,1.655]	0.121 [0.073,0.185]
Mean Mom's Investment Age 6	1.334 [1.306,1.358]	-0.836 [-0.857,-0.819]
Mean Mom's Investment Age 1	0.544 [0.511,0.599]	-0.336 [-0.361,-0.305]
Mean Dad's Investment Age 12	2.109 [2.071,2.156]	0.519 [0.471,0.603]
Mean Dad's Investment Age 6	1.932 [1.908,1.962]	-0.847 [-0.866,-0.829]
Mean Dad's Investment Age 1	0.928 [0.883,1.01]	-0.573 [-0.613,-0.517]

Notes: 90% confidence intervals based on 100 bootstrap replications in square brackets.

Table 3. Production of Cognition and Health with Endogenous Time Investments

	Cognition, Age 6	Health, Age 6	Cognition, Age 12	Health, Age 12
Cognition	-0.019 [-0.082,0.038]	0.013 [-0.077,0.026]	0.399 [0.288,0.435]	0.198 [0.154,0.315]
Health	0.946 [0.874,0.993]	0.961 [0.9,1.019]	0.406 [0.352,0.595]	0.685 [0.551,0.909]
Mom's Time	-0.113 [-0.211,0.046]	-0.043 [-0.119,0.168]	0.165 [0,0.264]	0.053 [-0.193,0.159]
Dad's Time	0.186 [0.036,0.273]	0.069 [-0.082,0.151]	0.03 [-0.121,0.173]	0.064 [-0.172,0.15]
Mom's Time Ctrl Func	-0.02 [-0.069,0.094]	-0.037 [-0.083,0.092]	0.02 [-0.034,0.066]	-0.023 [-0.186,0.017]
Dad's Time Ctrl Func	0 [-0.044,0.088]	-0.159 [-0.22,-0.031]	0.134 [0.006,0.211]	0.107 [-0.104,0.172]
Family Income	0.221 [-0.118,0.868]	0.416 [-0.438,0.736]	0.336 [0,0.635]	0.711 [-0.098,0.884]
White	0.128 [0.098,0.138]	-0.003 [-0.027,0.015]	0.082 [0.064,0.1]	0.024 [-0.007,0.035]
Female	0.08 [0.036,0.125]	-0.036 [-0.076,-0.004]	0.079 [0.061,0.129]	-0.004 [-0.045,0.042]
constant	0.084 [0.047,0.114]	0.018 [-0.012,0.051]	0.001 [-0.039,0.023]	-0.228 [-0.259,-0.189]
Residual Standard Error	1.568 [1.501,1.634]	1.465 [1.386,1.557]	0.707 [0.612,0.755]	0.785 [0.213,0.866]
	0.451 [0.426,0.479]	0.248 [0.202,0.294]	0.35 [0.32,0.386]	0.34 [0.304,0.599]

Notes: 90% confidence intervals based on 100 bootstrap replications in square brackets.

## 4.2 Counterfactual analysis

The counterfactual exercise is to set all paternal time investments equal. Policy analysis will be comparing how much child development inequality is reduced if all children receive an equal amount of fathers' time investment. We have 3 scenario of interventions. First, we set policy intervention to equalise the father's time spent when the child is aged 6 to 11. Second, we set policy intervention to equalise the father's time spent when the child is aged 12 to 18. Lastly, we set policy intervention to equalise the father's time spent for both stages, from age 6 to 18.

Table 4. Results on Counter-Factual Intervention

	Cognition std.	Health std.	Cognition std.(%)	Health std.(%)
No Invention	0.063	0.085	100.0	100.0
Invention in Age 6	0.059	0.078	92.7	92.4
Invention in Age 12	0.054	0.047	85.0	55.7
Invention In age 6 and 12	0.049	0.043	78.0	51.0

As shown in Table 4, this table compares the standard deviation of cognition and health

scores among individuals with different intervention experiences. The first column indicates whether the individual has had an intervention experience or not, and at what age. The second and third columns show the standard deviation of cognition and health scores, respectively. The fourth and fifth columns show the percentage of the standard deviation of cognition and health scores compared to the group with no intervention experience (i.e., 100%). From the table, it appears that individuals who have had an intervention experience at age 6 or 12 have a lower standard deviation in cognition and health scores than those who have not had an intervention experience. Specifically, individuals who have had an intervention experience at age 6 show a 7.3% lower standard deviation in cognition and a 7.6% lower standard deviation in health scores compared to the group with no intervention experience. Similarly, individuals who have had an intervention experience at age 12 show a 15% lower standard deviation in cognition and a 44.3% lower standard deviation in health scores compared to the group with no intervention experience.

## 5 Conclusion

Many studies and policy debates emphasize the trade-off of mothers between working and parenting on child development. This paper shows the substantial heterogeneity of father time spent with children. By using a nonlinear latent factor model, this paper suggests that such paternal heterogeneity explains 22% of cognition inequality and 49% of health inequality among children aged 1-13.

We plan for a few methodology improvements, and list here two aspects. The first is about improving the quality of our dataset. We plan to extend our dataset to include more measurements of household characteristics and activities. We also plan to use advanced techniques from the literature, e.g. matrix completion methods and simulated method of moments(SMM) to fill in the unobserved in the dataset due to the nature of PSID. The second is that we plan to use a more flexible parametric model or even a non-parametric model to characterize the joint distribution of the latent variables so as to relax the mixture gaussian assumption and increase the robustness of estimations in the later steps.

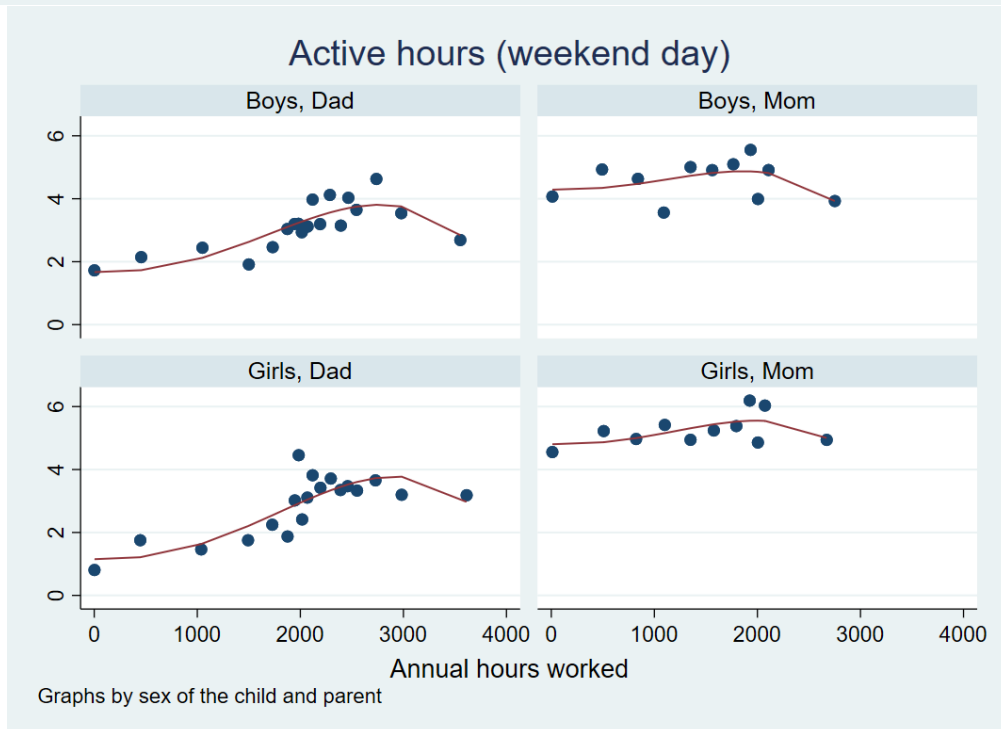
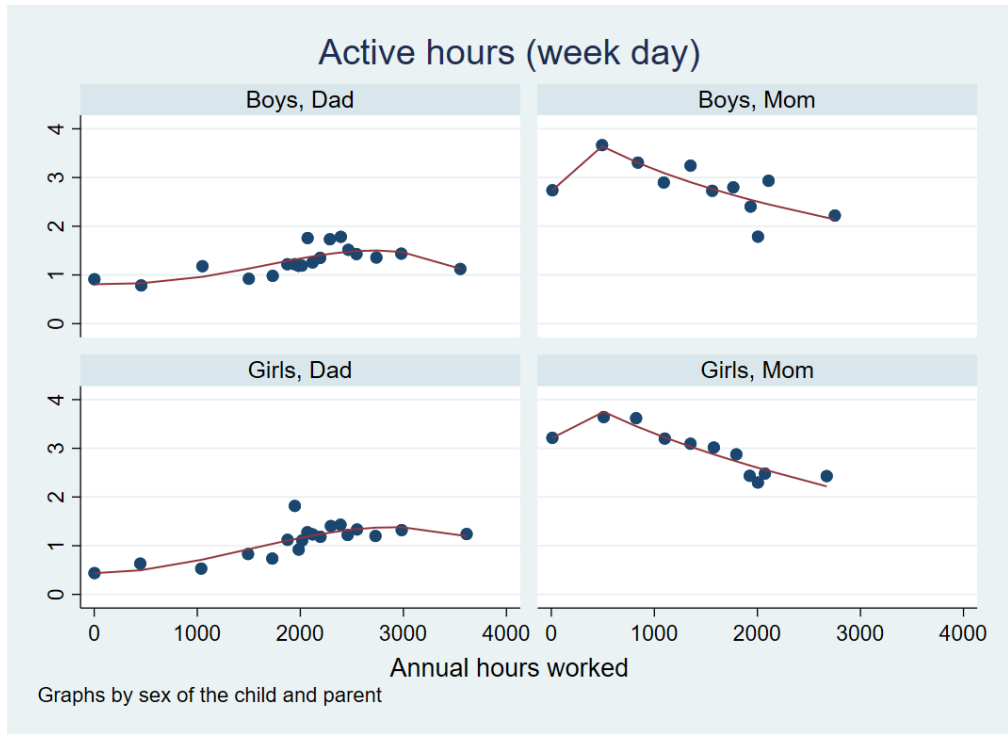
Furthermore, we will extend the analysis by incorporating collective household choices with the bargaining process between father and mother where child development is a public good. The bargaining parameter will be identified using private consumption items in PSID dataset. It may add additional understanding of how the bargaining process affects child development inequality.

## References

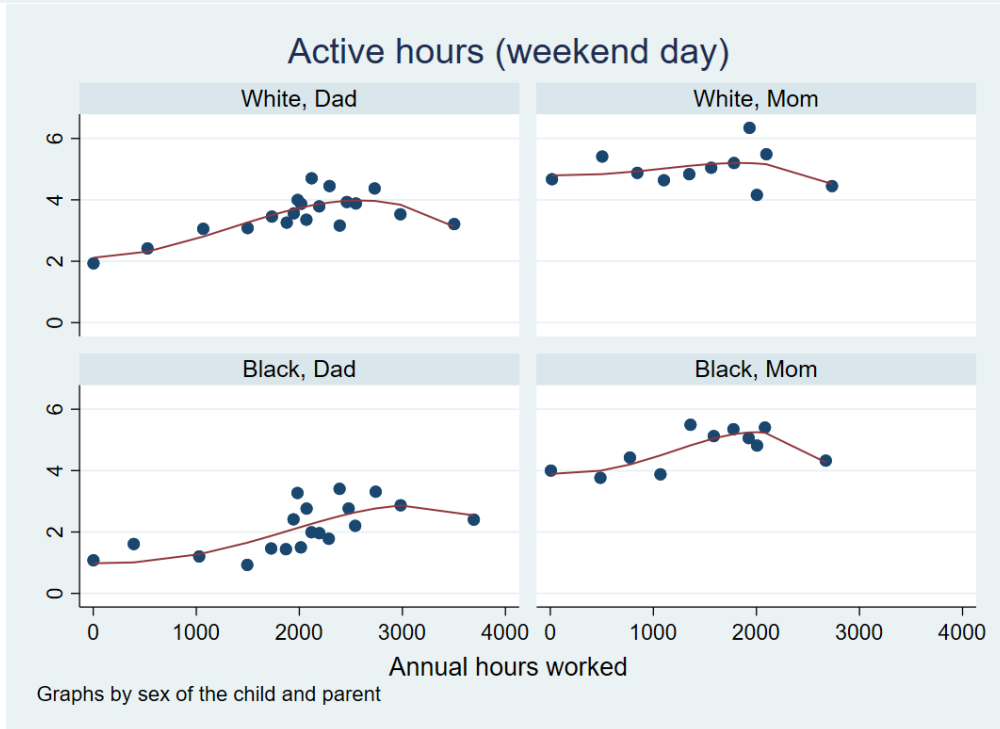
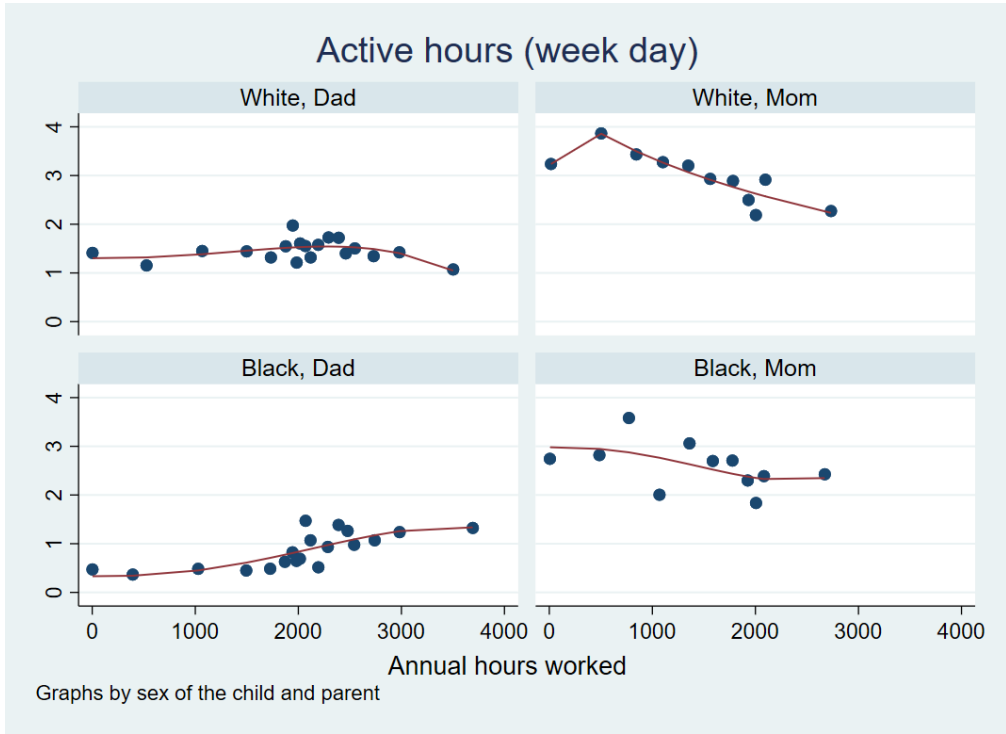
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## A Appendix Tables and Figures

Appendix Figure A1. Active parenting by sex of the child



Appendix Figure A2. Active parenting by race



Appendix Figure A3. Active parenting by age of the child

