# The Father and Child Inequality in Health and Cognition [*]

Jiaqi Li
University of Warwick [†]

Yaolang Zhong
University of Warwick [‡]

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**Abstract**

The literature on child development traditionally emphasizes maternal time use, female labor supply, and their impact on child outcomes. This study uncovers two key findings: First, fathers exhibit significantly greater variation in time spent with their children compared to mothers. Second, there is a strong positive relationship between fathers' labor market participation and their involvement in childcare—a trend not observed among mothers. This suggests that the long-assumed trade-off between labor market participation and childcare does not apply to fathers in the same way it does to mothers. To quantify the impact of this paternal time investment heterogeneity on child development inequality, this study estimates production functions for cognitive and health development in children aged 1-18, using data from both fathers and mothers in the PSID time diary and child development supplement. The analysis, based on a nonlinear latent factor model with gender-specific labor demand shocks as instruments, reveals a striking result: Eliminating paternal time investment heterogeneity reduces the variance in child cognition by 22 percent and child health variance by an impressive 49 percent, particularly among children aged 12-18. These findings underscore the significant role of fathers in child development and contribute to the literature on intergenerational mobility by investigating factors based on parental actions, rather than parental identity, with a special emphasis on the heterogeneity of fathers' time allocation.

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

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

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[†] Department of Economics, University of Warwick . Email: j.li.51@warwick.ac.uk

[‡] Department of Economics, University of Warwick. Email: yaolang.zhong@warwick.ac.uk

# 1 Introduction

Intergenerational mobility is one of central issues in economics, as it highlights the extent to which individuals can improve their economic prospects compared to those of their parents. The persistence of earnings between parents and children has been shown to be linked to parental characteristics such as income, education, socio-economic status, and wealth, as well as the genetic transmission of traits and the effect of wealth. In addition, such persistence is also interpreted as an indicator of lacking equal opportunities (Chetty et al., 2014; Blanden, 2019).

This study aims to investigate the extent to which intergenerational persistence is explained by what parents do, rather than who they are. Specifically, we examine the heterogeneity in the effects of parental investments on children's cognitive, health, and socio-emotional skills, with a particular focus on the differences between the effects of investment from mothers and fathers. This is an important area of research, as despite the crucial role that both parents play in child development, fathers' investments have often been overlooked in the literature.

To achieve this, we estimate a child development production function using two-stage control function approach estimation. This allows us to estimate the distributional productivity parameters of parental time investments, providing insights into how these investments affect intergenerational mobility.

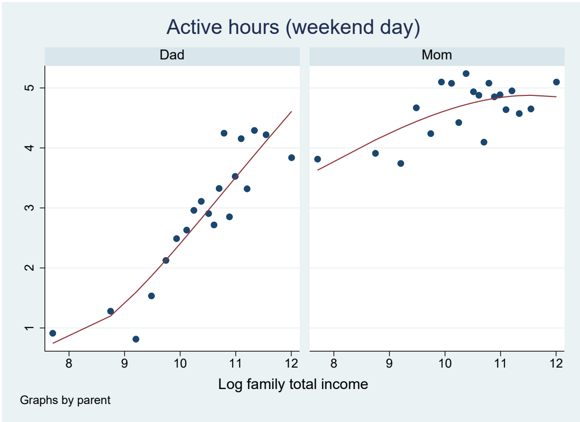
Parental investment is crucial for child development. Extensive research studies the relationship between maternal parenting time, female labor supply, and child development. Mothers face a trade-off to allocating time between parenting and work. Working more hours may increase consumption and expenditures 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 labor 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 modeling 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

Figure 1. Family income and weekend parenting hours

(a) Active parenting




(b) Passive parenting

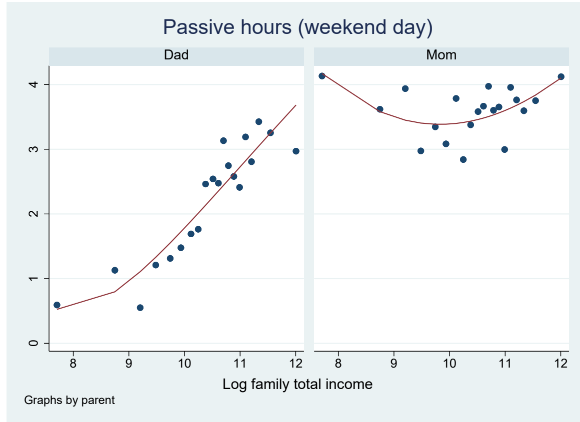
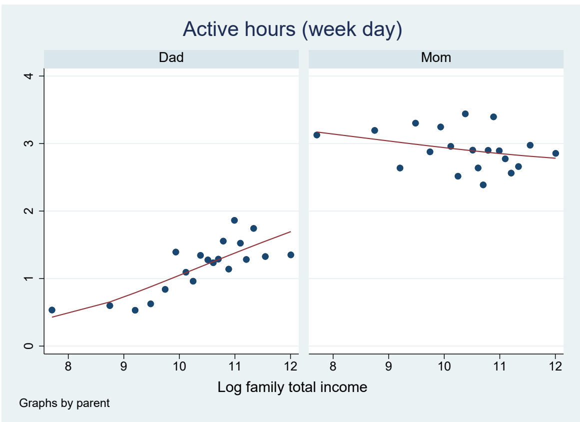
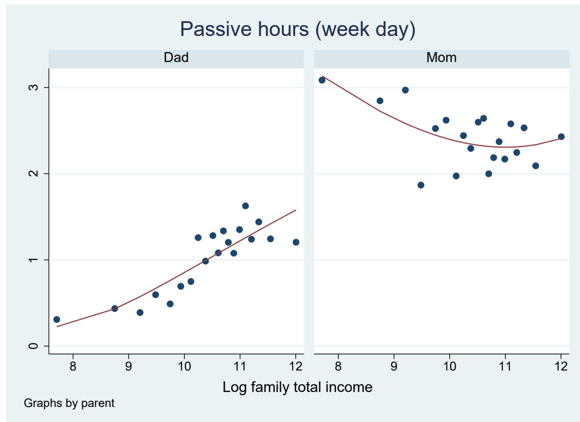



Figure 2. Family income and weekday parenting hours

(a) Active parenting




(b) Passive parenting




children's cognitive development. By contrast, the authors find money expenditures much less productive in fostering child development.

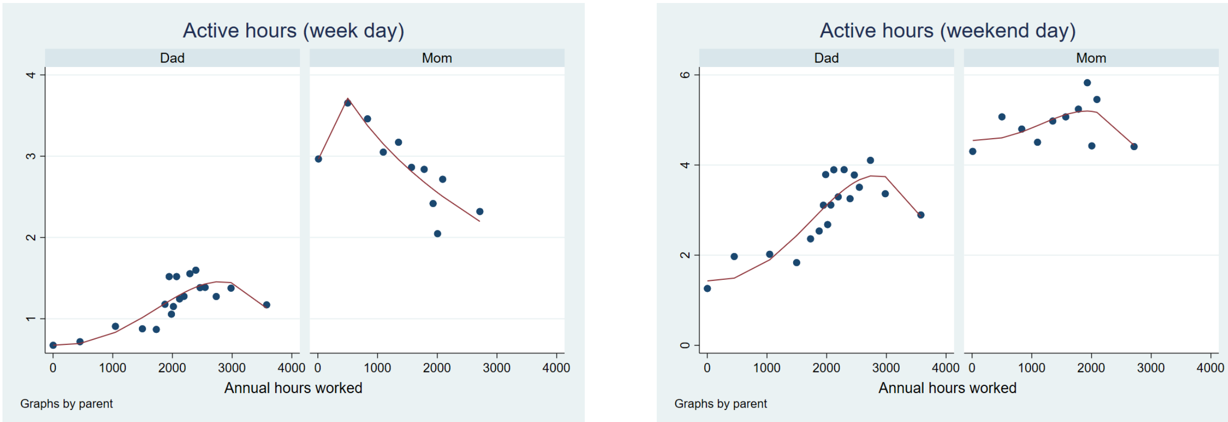
First of all, we document new stylized facts about fathers' time investment using a PSID time diary. We first highlight substantial heterogeneity in the father's time spent with the child, as shown in Figure 1 and 2. Furthermore, there is a strong positive association between family income and the father's 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[1].

Furthermore, the pattern is not driven by families with higher incomes having a larger

[1]We plan to add figures in the appendix for illustration in the later version of the paper.

Figure 3. Labor supply and parenting hours

(a) Week day (b) Weekend




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.

budget set to allow fathers to increase parenting and reduce hours worked. Instead, as shown in Figure 3, fathers working more hours in the labor market tend to spend more time with their children. Conversely, unemployed fathers tend to spend the least amount of time with their children 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.

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 labor 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 of 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 measurements collected. Among them, 1086 children are observed in all three years in 1997, 2001, and 2007.

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.

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

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.

Table 2. parenting hours 1997

| | Mean | SD | Max | Min |
|---|---|---|---|---|
| mother active hours on a weekend | 4.61 | 3.34 | 24.00 | 0.00 |
| father active hours on a weekend | 2.73 | 3.19 | 24.00 | 0.00 |
| mother passive hours on a weekend | 3.54 | 2.88 | 14.27 | 0.00 |
| father passive hours on a weekend | 2.04 | 2.58 | 14.27 | 0.00 |
| mother active hours on a week day | 2.90 | 2.55 | 24.00 | 0.00 |
| father active hours on a week day | 1.11 | 1.61 | 11.00 | 0.00 |
| mother passive hours on a week day | 2.43 | 2.26 | 16.17 | 0.00 |
| father passive hours on a week day | 0.95 | 1.47 | 16.00 | 0.00 |
| Observations | 2904 | | | |

Note: 1997 PSID-CDS Time Diary

## 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 psychical 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, an 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), express appreciation, have favorite 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. The child diary records all activities of the child throughout the entire day, including beginning time, ending time, activity type, location, and social contact engaged in the activities. Parental involvement is further distinguished by passive and active participation. Each child has the diary measured both on a weekday and a weekend day.

### 2.5 Family environment

Two domains measure the family environment. First is the set of measures of family conflict, such as the calmness of family discussion, frequency of family fights, frequency of family hit, and frequency of family throwing things. The second domain is the cognitive simulation of the home scale. This includes the number of books read past year, the number of books in the house, and the number of cellphones in the house. The third domain is home and neighborhood including the noise inside the house, the noise outside the house, and the cleanliness of the house.

### 2.6 Instruments for the 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 state, and gender. We assume that the deviation from linear prediction reflects local labor 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 standardized to have a mean of 0 and a standard deviation of 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.

$$H_a = H\left(\theta_a^c, \theta_a^h\right) \tag{1}$$

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.

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

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 the child's stage by $t$. Following Cunha et al. (2010), we assume a CES function. Therefore, we have that

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

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

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

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 maximization 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 arises 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

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

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 labor 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 fathers 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 measures and latent variables:

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

In a matrix form:

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

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.

$$F_\theta = \tau\Phi\left(\mu_A, \Omega_A\right) + (1-\tau)\Phi\left(\mu_B, \Omega_B\right) \tag{9}$$

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:

$$F_M = \tau\Phi\left(\Pi_A, \Psi_A\right) + (1-\tau)\Phi\left(\Pi_B, \Psi_B\right) \tag{10}$$

where

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

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:

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

## 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 $\mu_A, \mu_B$.

(iii) With the joint distribution in hand, we draw a synthetic dataset to estimate the parameters of interest in the dynamic system of equations, i.e. the production functions at different stages, using the control function approach.

# 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 3, 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 4, 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 4 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 3. Mixture Weights and Means

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

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

Table 4. Production of Cognition and Health with Endogenous Time Investments

| | Congition, Age 6 | Health, Age 6 | Congition, 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] |
| | 0.221 [$-0.118$,0.868] | 0.416 [$-0.438$,0.736] | 0.336 [0,0.635] | 0.711 [$-0.098$,0.884] |
| Family Income | 0.128 [0.098,0.138] | $-0.003$ [$-0.027$,0.015] | 0.082 [0.064,0.1] | 0.024 [$-0.007$,0.035] |
| White | 0.08 [0.036,0.125] | $-0.036$ [$-0.076$,$-0.004$] | 0.079 [0.061,0.129] | $-0.004$ [$-0.045$,0.042] |
| Female | 0.084 [0.047,0.114] | 0.018 [$-0.012$,0.051] | 0.001 [$-0.039$,0.023] | $-0.228$ [$-0.259$,$-0.189$] |
| constant | 1.568 [1.501,1.634] | 1.465 [1.386,1.557] | 0.707 [0.612,0.755] | 0.785 [0.213,0.866] |
| Residual Standard Error | 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 5. 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 5, 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 invention 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 three 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. Thirdly, we plan to use quantile regression approach on the production function estimation to quantify the contribution of parental investment in a distributional level.

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.

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# A Appendix Data

The Child Development Supplement to the PSID obtained the following: (i) reliable, age graded assessments of the cognitive, behavioral, and health status of 3,600 children (including about 250 immigrant children) obtained from the mother, a second parent or parent figure, the teacher or childcare provider, and the child; (ii) a comprehensive accounting of parental and caregiver time inputs to children as well as other aspects of the way children and adolescents spend their time; (iii) teacher-reported time use in elementary and preschool programs; and (iv) other-than-time use measures of other resources–for example, the learning environment in the home, teacher and administrator reports of school resources, and parent-reported measures of neighborhood resources.