Intergenerational Transmission of Time Preferences: An Evidence from Rural Thailand

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Abstract

This study investigates factors associated with child time preferences in rural Thailand using a large and unique data set of more than 700 children with rich background information on child, caregiver, parent, and household characteristics. We find that the caregiver discount factor positively correlates with a child's ability to delay gratification, regardless of whether the caregiver is a parent. Children's age and literacy ability are significantly associated with child time preferences, while other variables, e.g., screen time, are not. Interestingly, the older the caregivers, the stronger the relationship between caregiver and child time preferences.

Keywords: time preferences; patience; field experiment; intergenerational transmission; skill formation

JEL Codes: C93; D64; J24; O15

1 Introduction

Time preferences play an essential role in intertemporal decision-making, which involves costs and benefits that occur at different points in time, e.g., health behaviors and outcomes (e.g., Bradford et al., 2017; Chabris et al., 2008; Kirby and Petry, 2004), financial decisions (e.g., Ashraf et al., 2006; Meier and Sprenger, 2010, 2013), and human capital formation (e.g., Cadena and Keys, 2015). Time preferences also correlate to child and adolescent behaviors and life outcomes, e.g., savings, expenditures on smoking and alcohol and conduct at school (e.g., Sutter et al., 2013), performance at school (e.g., Castillo et al., 2011; Falk et al., 2021), high school completion (e.g., Castillo et al., 2019) and lifetime outcomes (e.g., Cadena and Keys, 2015; Golsteyn et al., 2014). A child's ability to make optimal intertemporal choices is crucial since such decisions determine later life outcomes. It is, therefore, important to understand how time preferences are shaped during young ages.

Several factors could contribute to child time preferences, from parent, caregiver, and household characteristics to teacher input and the school curriculum. In this study, we use RIECE panel data, an early childhood panel in rural Thailand setting, which contains rich background information about child, caregiver, parent, and household characteristics to investigate factors associated with a child's ability to delay gratification. More importantly, approximately 46% of children in this setting live in a household without the permanent presence of any parent. This phenomenon is common in Thai rural areas where parents seek employment in big cities to support the family and have to leave their children at home, primarily to grandparents or other relatives (Ingersoll-Dayton et al., 2018; Dinh and Kilenthong, 2021). This study could, therefore, examine the role of caregiver time preferences on child time preferences in a unique, unexplored setting.

There is still limited evidence regarding the correlation between child and caregiver time preferences. Previous studies focus on the transmission between parents and their children, and findings are still inconclusive. Chowdhury et al. (2022) measured child and parent time preferences in Bangladesh by asking them to choose between sooner smaller and later larger rewards (multiple price list method) and found that child time preferences correlate to both mother and father time preferences. Along the same line, Falk et al. (2021) and

Kosse and Pfeiffer (2012) found a significant relationship between child and mother time preferences in Germany; however, in Falk et al. (2021) mother time preferences were elicited by a validated non-incentivized questionnaire. Brenøe and Epper (2022) used data from the Danish Longitudinal Survey of Youth (DLSY) and DLSY-Children, which measured time preferences of parents and children with the same non-incentivized questions regarding jobs but in different years (1973 for parents and 2010 for children) and found a robust transmission from parents to children. In contrast, Andreoni et al. (2019) and Bettinger and Slonim (2007) did not find a significant relationship between child and caregiver time preferences measured by the multiple price list method. While all caregivers in Bettinger and Slonim (2007) were biological parents, and in Andreoni et al. (2019) 94% of caregivers were either mothers or fathers.

It is still unexplored whether this relationship exists only between children and parents or is merely about caregiving, so it would also be present when caregivers are not parents but other family members. Also, previous studies did not consider several factors, such as a child's math and literacy ability, sleep, and screen time. This study aims to investigate whether the relationship between child and caregiver time preferences exists when a caregiver is not a parent and explore the other contributing factors of child time preferences. Also, we investigate which factors might affect the correlation between child and caregiver time preferences.

Our contributions are twofold. Firstly, with different types of caregivers (parents or not) in our sample, we are the first to investigate whether having a parent as a primary caregiver matters for child time preferences. Secondly, using data from the RIECE panel survey, we have richer background information than previous studies about children, caregivers, parents, household characteristics, and time spent on sleep, screen, and active activities. Subsequently, we can explore comprehensive potential factors for a child's ability to delay gratification. Also, we can estimate the caregiver discount factor using a theoretical formulation and disaggregate household consumption data instead of aggregate consumption as in, e.g., Andersen et al. (2008, 2014).

Our study finds a significant relationship between child and caregiver time preferences regardless of whether a primary caregiver is a parent. Moreover, the caregiver's age has a positive effect on this relationship. In addition, among a broad set of variables (including sleep and screen time), only a child's age and literacy ability are significantly positively associated with a child's ability to delay gratification.

The rest of the paper is organized as follows. Section 2 describes our empirical methodology, i.e., our sample, child, and caregiver time preferences measurement, and model specifications. Section 3 presents the main results regarding intergenerational transmission of time preferences and heterogeneous effects. Finally, in section 4, we discuss and conclude the study. The Online Appendix presents supplementary materials.

2 Data, Measurement and Empirical Specification

This paper uses early childhood panel data from rural Thailand, called RIECE panel data, covering 21 Tambons or sub-districts in Mahasarakham province and two Tambons in Kalasin province.[1] The children samples were zero-to-six years old at the baseline survey 2016. RIECE panel data provide rich and comprehensive background information about children, their caregivers, parents, and households, which allows us to examine a richer set of potential contributing factors to child time preferences more than previous studies.

In addition to the regular annual survey, we conducted time preference elicitation tasks with children and caregivers. See the details of each task below. We were able to test 1,115 children and 966 adults in the household.

2.1 Child Time Preferences

This section describes the procedure of the elicitation task for children and provides basic descriptive statistics.

2.1.1 Elicitation Tasks for Children

Elicitation tasks to measure time preferences for kindergarten and primary school children are slightly different as follows.

[1] There are between 8 and 24 villages in a Tambon in the survey areas, with an average of 14 villages. See details of the panel at https://riped.org/data/riece-panel-data/.

Kindergarteners

For kindergarten children, we used a variant of the original marshmallow test (e.g., Mischel et al., 1972) to measure time preferences, the ability to wait for a later larger benefit in the future. Children were offered a binary choice between getting ONE unit of their favorite item (chosen before the task started) TODAY or waiting to get TWO units of the same item TOMORROW.

Primary Schoolers

For primary school children, we used a variant of the convex time budget method (e.g., Andreoni and Sprenger, 2012; Sutter et al., 2022). Children were asked to choose one option from the following three alternatives. In option 1, children would get TWO units of their favorite item TODAY and nothing TOMORROW. In option 2, children would get ONE unit TODAY and TWO units TOMORROW. And in option 3, children would get nothing TODAY and FOUR units TOMORROW. To pool both kindergarteners and primary school children in the same main analysis, we categorize option one as impatience and option two and option three as patience.

2.1.2 Procedure

We conducted the incentivized task with 832 kindergarten and 283 primary school children, aged between 3-9 years (mean=5.95; SD=1.27), one-on-one in an isolated room at their schools during school time between November 2018 and May 2019. Two or three children entered the room around the same time but then sat separately far enough and faced a corner or a wall so they could not hear or see other children's decisions. Before we started the elicitation task, we asked children to choose their favorite items from the following items: different types of sweets (e.g., chocolate, marshmallow, jelly, etc.) or stationery (e.g., pencil, colored pencil, eraser, etc.). Then we explained the rules of the task and asked test questions: "If you choose to receive the reward today (tomorrow), how many unit(s) will you get?" If the child gave the correct answer, we proceeded with the task. If not, we explained the whole task to the child again. We repeated the explanation at most three times. Around 97 percent of 1,115 children (N=1,078) passed the test question, resulting in a sample of 1,078 children who had validated test results, called the whole sample.

The children received the TODAY reward in a bag immediately after completing all activities. On the other hand, they would receive the TOMORROW reward in a different-colored bag labeled with their names from their teachers tomorrow. In some sessions conducted on Fridays, the children had to wait until the following Monday (21.06% of the whole sample). We control for the days of the week on which the task was conducted in our regressions on the child's decision to wait and find that none of the days of the week are significantly different from Friday.

Figure 1 shows the distribution of "waiting" choice across a child's age (in years). The fraction of children who waited increases with age, starting at five. Surprisingly, the fraction of waiting choices of children aged five years drops from that of children aged four. This u-shaped pattern is consistent with findings from Chicago Heights in Andreoni et al. (2019), where they argued that children younger than five years old might not yet fully understand the concept of "tomorrow" with support of findings in Suddendorf and Busby (2005). In addition, Labrell et al. (2020) reviewed previous studies and suggested that children's temporal concepts and time judgment start to establish at around five years of age.

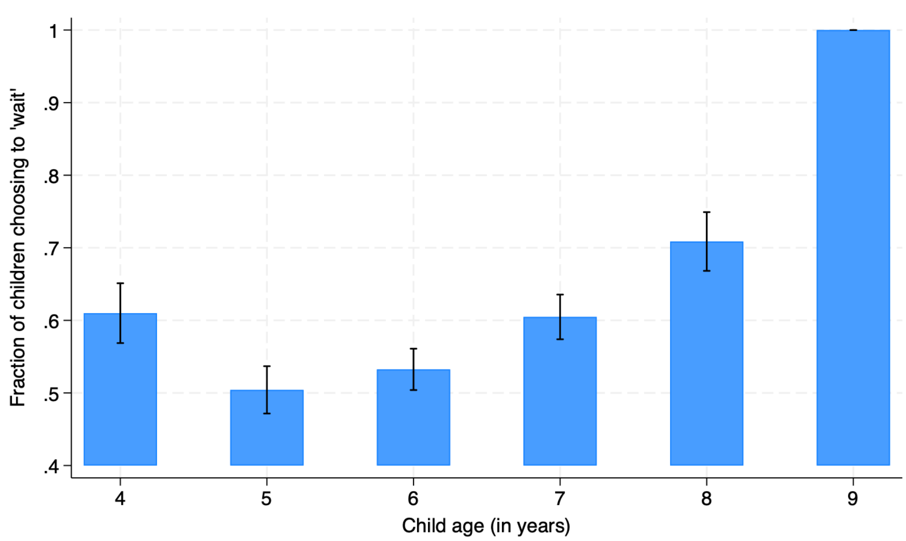

Figure 1: Fraction of children choosing to wait for a later larger reward across age (years) for the whole sample

As a result, this paper dropped children younger than five (N=146). In addition, we dropped children nine years old and older (N=8) since there was no variation in their choices. In addition, to study intergenerational transmission, we matched the children with their primary caregivers. This step led to a sample of 809 children. Some samples (N=100) were dropped in the main analysis due to missing data. In the end, the main sample in the study consists of 709 children. Table 2 shows that key characteristics of children in the main and the whole samples are statistically indistinguishable. In the main sample, 47.2% were female, and 44.7% chose sweets as their favorite item over stationery. Regarding our measure of child time preferences, 56.8% of children decided to wait for a later larger reward.

2.2 Caregiver Time Preferences

We used the multiple price list method to elicit caregiver time preferences (Andersen et al., 2008; Coller and Williams, 1999; Harrison et al., 2002; Sutter et al., 2013), based on the following quasi-hyperbolic discounting function (Laibson, 1997):

$$V_{i,t} = U\left(c_{i,t}\right) + \beta_i \delta_i \left[U\left(c_{i,t+1}\right) + \delta_i U\left(c_{i,t+2}\right)\right] \tag{1}$$

where $U(c)$ is the period-utility from the consumption c; t is the present period; δ_i is the long-run discount factor; and β_i is the time-consistent parameter. If an individual is time-consistent, then $\beta_i = 1$, and the discounting function takes the classic exponential form. On the other hand, the individual is present-biased (future-biased) if $\beta_i < 1$ ($\beta_i > 1$).

2.2.1 Elicitation Task for Adults: Multiple Price List Method

Participants were asked to choose between a sooner smaller payoff in option A and a later larger reward in option B in each decision. There were two choice sets, each comprising six decisions, making 12 decisions in total.

In choice set 1, we asked participants to choose between the sooner reward $M_t = 100$ Thai Baht (THB)[2] in next month and a later larger reward M_{t+1} in two months with six

[2]Given that the purchasing power parity (PPP) conversion factor (GDP) was 12.618 Thai Baht per 1 USD in 2019, this amount is equivalent to the purchasing power of 7.89 US Dollar – USD PPP. See https://data.worldbank.org/indicator.

different scenarios as shown in Table 1. Choice set 2 was similar except for the payment dates, which were "today" for option A and "next month" for option B. The order of both choice sets was random (42.3% of the main sample played set 1 first).

Table 1: Price list in choice set 1

Decision	Option A THB next month		Option B THB in 2 months	Monthly interest rate (%)
1	100	or	105	5
2	100	or	110	10
3	100	or	120	20
4	100	or	130	30
5	100	or	150	50
6	100	or	200	100

Note that the last column was not shown to the participants.

Regarding the payment, only one out of the 12 decisions was randomly drawn by two dice rolls to determine the actual payoff. The first roll was to choose the choice set randomly. The second roll randomly selected one of the six decisions in the randomly chosen choice set. The participants received the payoff according to the selected option in the randomly drawn decision. With this mechanism, all decisions were equally relevant for the payoff, and income effects (generated from the task) could be avoided (Charness et al., 2016). This random mechanism was known to all participants.

2.2.2 Procedure of Multiple Price List Method

We conducted the incentivized task with 966 caregivers one-on-one at home during the annual RIECE panel household survey between June and November 2019.[3] This sample constitutes the whole sample of caregivers. The average earning from this time preference elicitation task for all participants was 121.04 (SD=32.54) THB (9.59 USD PPP). Figure 2 shows the fraction of participants for each number of waiting choices. A participant with six (zero) waiting choices means he/she always chose option B (A) in all six items in a particular choice set. We can see that the distributions of waiting choices in set 1 (one month vs. two

[3]We conducted pilots with 17 participants in the target area in late May 2019 to test the task, questions, and procedure and train our enumerators.

months) and set 2 (today vs. one month) are not identical, suggesting that there were some time-inconsistent participants.

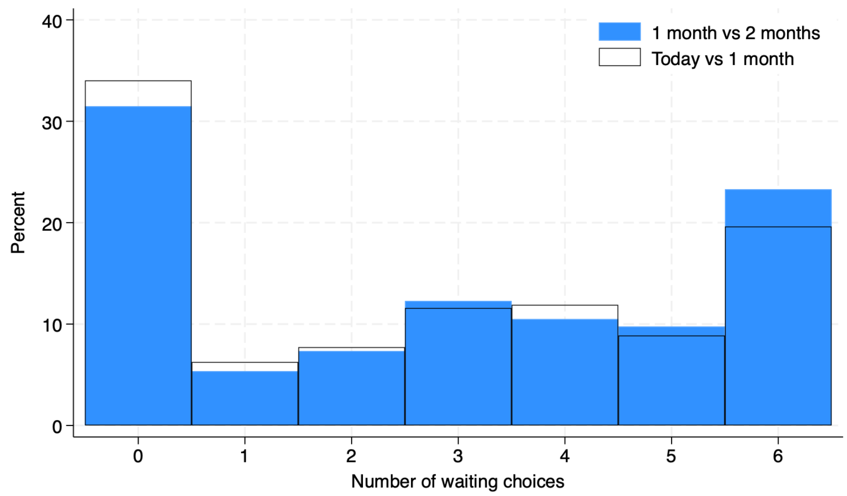

Figure 2: Fraction of adult participants for each number of waiting choices in both sets for the whole sample of caregivers

Concerning the issues of trust and transaction cost that might confound participants' intertemporal decisions, we followed the following procedure. First, this task was integrated into the annual RIECE panel's household survey, in which participants had participated for four years. Second, "today" payoffs were not paid immediately during the survey but in the evening on that day, and all payoffs, including those of "today", were paid via bank transfers to keep trust and transaction costs homogeneous across all options.

As discussed earlier, we matched the children with their primary caregivers to study intergenerational transmission. Only 754 primary caregivers could be matched with the children, who were five to eight years old and passed the test question. Note that some of them were matched with multiple children. When there was more than one adult at home, we performed the task with an adult who provided the most care to the child and defined this person as the primary caregiver. Some caregivers (N=95) were dropped in the main analysis due to missing data. In the end, the main sample of caregivers in the study consists of 659 adults.

2.2.3 Calculation of Effective Discount Factors

We calculated time preference parameters using the same principle as in Andersen et al. (2008). An individual i with utility function U, is indifferent between the sooner reward M_t and the switching later reward M_{t+1} if and only if

$$U\left(c_i + M_t\right) + \delta_i^* U\left(c_i\right) = U\left(c_i\right) + \delta_i^* U\left(c_i + M_{t+1}\right) \tag{2}$$

where the effective discount factor $\delta_i^* = \delta_i$ for set 1 (the long-run discount factor), $\delta^* = \beta_i \delta_i$ for set 2, and c_i is monthly consumption per-capita of household i. Household consumption is calculated from household expenditures in five essential categories, namely food, utilities, recreation, education, and clothes, and then divided by the number of members in the household. The expenditures include values from purchases, produces, and presents. The main sample's average monthly consumption per capita was 2,560 (SD=1,668) THB (202.88 USD PPP). Note that the richness of our household data allows us to incorporate individual heterogeneity in consumption c_i while most of the previous studies, e.g., Andersen et al. (2008, 2014), could not.

The utility function is assumed to be separable and stationary over time. The left-hand side of the equation (2) represents the discounted utilities from choosing the sooner smaller payoff delivering at time t. In comparison, the right-hand side is the discounted utilities from choosing the later larger payoff delivering in $t+1$ month(s). This indifferent condition implies that an individual facing an increasing and continuous sequence of later reward options will switch from the sooner reward to the later reward at M_{t+1}.

To determine an individual "long-run" discount factor, δ_i, we focus on decisions in choice set 1, which does not involve any immediate payoff. To do so, we need to assume the functional form of the utility function. We take two functional forms as follows.

Logarithmic Form with Background Consumption

Based on the benchmark result in Andersen et al. (2008), it is reasonable to assume that the discounted utility function is in the following logarithmic form:

$$U\left(c\right) = \ln c \tag{3}$$

Therefore, the effective discount factor, δ_i^*, that satisfies the indifferent condition (2) is as follows.

$$\delta_i^* = \frac{\ln\left(1+\frac{M_t}{c_i}\right)}{\ln\left(1+\frac{M_{t+1}}{c_i}\right)} \tag{4}$$

Practically, each player faces a discrete choice of M_{t+1} (not a continuous one). Therefore, we approximate the switching later reward using the average between the later larger payoff at the switching point[4], M_{t+1}^{j}, and that at the previous point, M_{t+1}^{j-1}. As a result, for an individual who switched her/his choice to the later reward at the option M_{t+1}^{j}, the value of her/his effective discount factor, δ_i^*, is as follows.

$$\delta_i^* = \frac{\ln\left(1+\frac{100}{c_i}\right)}{\ln\left(1+\frac{M_{t+1}^{j-1}+M_{t+1}^{j}}{2c_i}\right)} \tag{5}$$

Linear Form without Background Consumption

Alternatively, we assume that the discounted utility function takes a linear form. As a result, an individual does not take background consumption into account while deciding in the time elicitation task (as in Meier and Sprenger, 2010, for example). Then, we calculate the effective discount factor, which satisfies the following conditions:

$$U\left(M_t\right) = \delta_i^* U\left(M_{t+1}\right) \tag{6}$$

Again, using the switching point data, we can easily compute the effective discount factor as follows.

$$\delta_i^* = \frac{M_t}{M_{t+1}} \tag{7}$$

Then, for an individual who switched her/his choice to the later reward at the option M_{t+1}^{j}, the value of her/his effective discount factor, δ_i^*, is as follows.

$$\delta_i^* = \frac{M_t}{\frac{M_{t+1}^{j-1}+M_{t+1}^{j}}{2c_i}} \tag{8}$$

[4]For those who switched multiple times (around 25%), we use their first switching point to estimate their discount factor. In the regression analysis, we also control for "having switched back and forth" or choice inconsistency by a dummy variable. In the robustness check, we also dropped choice-inconsistent caregivers. The regressions yield qualitatively similar results. See the Online Appendix.

In addition to calculating the effective discount factor, we use the number of "waiting choices" in set 1 (one month vs. two months) as another proxy of the long-run discounting indicator. The number ranges from 0 (the individual did not wait in any decision in set 1) to 6 (the individual waited in all six decisions in set 1).

2.2.4 Calculation of Time-Consistency Parameter

The time-consistency parameter of an individual i, β_i, can be calculated by dividing the effective discount factor in the immediate time frame (set 2), $\beta_i\delta_i$, by that in the future time frame (set 1), δ_i.

$$\beta_i = \frac{\beta_i\delta_i}{\delta_i}. \tag{9}$$

The time-consistency indicator is measured by categorizing caregivers into three groups according to their (first) switching point (from option A to option B) in set 1 and set 2 when we apply the number of "waiting choices" in set 1 as a proxy of the long-run discounting indicator. The individual is time-consistent when she/he has the same (first) switching point in both sets, indicating that she/he has the same discount factor for future (set 1) and immediate (set 2) time frames. The individual is present-biased when she/he has a later (first) switching point in set 1 than in set 2, indicating that she/he can wait more in the future time frame (has a higher discount factor) than in the immediate time frame. The individual is future-biased in the opposite situation.

2.2.5 Descriptive Statistics for the Elicitation Task for Adults

Out of 659 primary caregivers[5] in the main sample, 90% were female; the average age was 50.9 (SD=12.7) years old; 7.7% declined the actual payment from the task; 42.3% played choice set 1 before set 2; 74.8% were choice consistent, i.e., switched from option A to B at most once.

The average of the long-run discount factor of the main sample, δ_i, based on a log utility function with background consumption (I) is 0.78 (SD=0.21) with a median of 0.87, while the one based on a linear utility function without background consumption (II) is 0.77

[5] Note that some caregivers take care of multiple children.

(SD=0.21) with median 0.87. The average number of "waiting choices" in the choice set 1 is 2.97 (SD=2.40), with a median of 3. See Figure 3 for the distribution of the estimated long-run discount factors based on log and linear utility functions (namely, discount factors I and II, respectively).

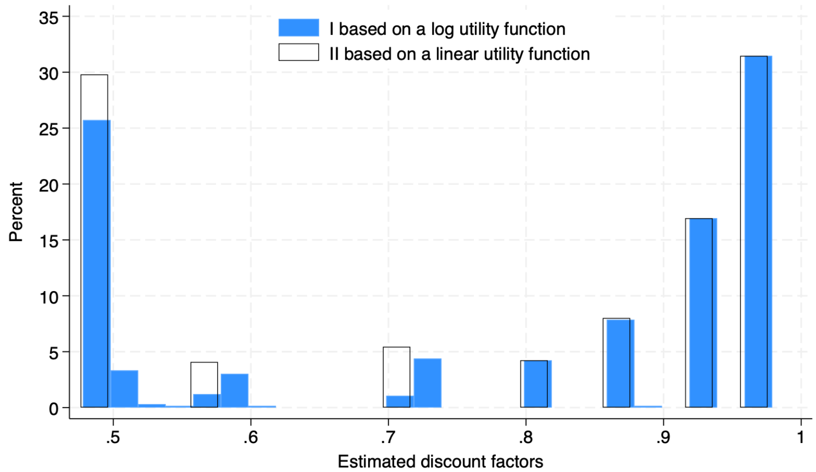

Figure 3: Distributions of caregiver's long-run discount factors based on logarithm (blue) and linear utility functions (white) for the main sample of caregivers

Regarding the distribution of the time-consistency parameter, see Figure 4 for the estimated parameters based on log and linear utility functions (time-consistency parameters I and II, respectively). The mean of both parameters is 1.02 (SD=0.31) with a median of 1. Regarding the category measure of time-consistency, 46.6% of 659 caregivers are time-consistent, while 30% and 23.3% are present-biased and future-biased, respectively.

2.3 Empirical Specifications

The main analysis estimates the following linear model:

$$TP_i^c = \alpha_0 + \alpha_1 \delta_i^p + \alpha_2 \beta_i^p + \boldsymbol{\alpha}_3 \boldsymbol{X}_i + \varepsilon_i, \tag{10}$$

where TP_i^c is a dummy variable indicating that child i chose to wait for a later and larger reward or not, which is a proxy of his/her time preferences; δ_i^p is a caregiver's long-run discount factor; β_i^p is a caregiver's time-consistency parameter; $\boldsymbol{X}_i$ is a vector of control

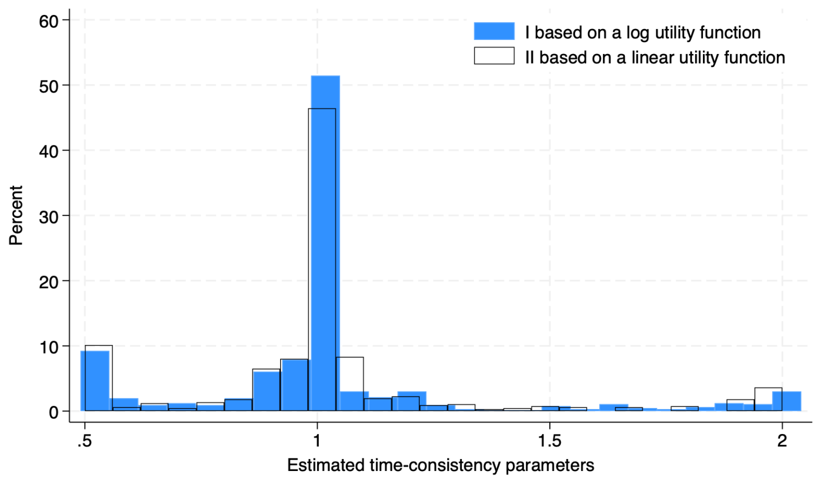

Figure 4: Distributions of caregiver's time-consistency parameters based on logarithm (blue) and linear utility functions (white) for the main sample of caregivers

variables including child age (in months), child gender, and cognitive ability, proxied by age-standardized math and literacy ability[6], child's reward choice (whether a child chose sweets as a reward), and household wealth[7]; and ε_i is an error term.

Provided that the outcome variable, child time preferences TP_i^c, is a dummy variable, we estimate the model using linear probability and Probit regressions. All estimations are clustered at the school level to account for unobserved within-school correlation.

We perform robustness checks of the main results by using several measures of δ_i^p and β_i^p, described above, and adding more control variables, including whether the caregiver is a parent, whether only one parent lives in the household, whether both parents live in the household, whether parents are divorced, being the only child, being the first-born child, number of siblings; caregiver's age (in years), caregiver's gender, and caregiver's years of education, age-standardized screen time (for both internet and television), age-standardized sleep time, and age-standardized activity time with the caregiver[8], interviewers fixed effects,

[6]Math and literacy ability were directly assessed using school readiness assessment during RIECE panel data's annual survey and was standardized by age (see examples of the assessment items in Kilenthong et al., 2023).

[7]Household wealth is measured by the number of household assets including pickup trucks, motorcycles, mobile phones, color TVs, and fans using a confirmatory factor analysis (CFA).

[8]Activity time in this study means time spent on interactive activities between child and caregiver, which include reading, story-telling, outdoor playing, sport, role-playing, learning, drawing, field trips, and doing

"day of the week", whether the caregiver wished to receive a payoff from the task, and whether a caregiver is choice consistent (switched at most once and from option A to B). See Table 2 and 3 for descriptive statistics of all control variables.

We also investigate whether the intergenerational transmission between child and caregiver time preferences is heterogeneous across subgroups. The heterogeneous effects are estimated using the following model:

$$TP_i^c = \gamma_0 + \gamma_1 \delta_i^p + \gamma_2 \beta_i^p + \gamma_3 \delta_i^p \times H_i + \gamma_4 H_i + \boldsymbol{\gamma}_5 \boldsymbol{X}_i + \varepsilon_i \tag{11}$$

where H_i is a subgroup characteristic of interest capturing the heterogeneity, including parent characteristics, i.e., whether only one parent lives in the household, whether both parents live in the household, whether the caregiver is a parent, and whether parents are divorced; caregiver characteristics, i.e., caregiver's age, education, and whether the caregiver has the same gender as the child; child characteristics, i.e., child's age, gender, math and literacy ability (age-standardized), whether the child is the only child, first-born child, and number of siblings; time-spending characteristics (categorized as high or low by median split), i.e., screen time (for both internet and television), sleep time, and activity time between child and caregiver; and wealth. These subgroup characteristics are considered each one at a time. As for the main model, we estimate the model using linear probability and Probit regressions. All estimations are clustered at the school level to account for unobserved within-school correlation.

3 Results

Table 4 shows that caregiver time preferences, represented by the caregiver's long-run discount factor I, are significantly and positively correlated with child time preferences. The results suggest that a ten percentage point increase in the caregiver's long-run discount factor is associated with a two percentage point increase in the probability that his/her child will wait for a later larger reward. In other words, patient caregivers tend to have patient children. However, caregivers' time-consistency parameter is not significantly associated with

homework. These variables were categorized as high or low by median split.

children's ability to wait. This is generally true for the OLS (models I-II) and Probit regressions (models III-IV). Similarly, results are robust when the caregiver's discount factor I is replaced by long-run discount factor II, which is calculated based on a linear utility function without background consumption, and the number of waiting choices, as shown in Table 5 and 6, respectively. See full regressions results in the Online Appendix.

Significant covariates are the child's age and (age-standardized) literacy ability, which indicates that older children and children with higher language capability (relative to children of the same age) can wait significantly longer. Other children-related covariates have insignificant coefficients. Being a girl and (age-standardized) math ability seem to be positively correlated with the ability to wait, while the association tends to be negative for household wealth. Regarding parenthood, being a parent and having one or both parents living at home (relative to none of the parents at home) positively correlate with a child's decision to wait, but not significantly. In addition, neither sleep time nor screen time is significantly correlated to a child's ability to wait or other caregiver's characteristics.

The estimation results, especially for caregiver time preferences, are robust when choice-inconsistent caregivers (those who switched multiple times) are excluded when school-fixed effects regressions are employed, when standard errors are clustered at the household level, and when choices of the primary children in time preference elicitation task were differently defined[9] See the Online Appendix.

Table 7 presents the heterogeneous effects with respect to parent, caregiver, child, and household characteristics as well as time-spending controls. The only consistent and significant heterogeneous effect is the differential impact of the caregiver's age; see the fifth row in table 7. The interaction term between caregiver time preferences and caregiver's age is positive and significant. In other words, the relationship between children and caregiver time preferences is stronger for older caregivers. One potential explanation for the stronger relationship is that older caregivers have more time to spend with the child. The natural way to examine this issue is to check the interaction term between time preference measures and activity time. Indeed, this interaction term is positive but not statistically significant.

[9]Instead of grouping option 2 and 3 as patience, only option three was classified as patience here.

4 Discussion and Conclusion

This study measures child time preferences using a binary delay gratification task and caregiver time preferences using the multiple price list method. Our main advantage is that we can conduct field experiments on the subjects of an ongoing panel data survey, namely the RIECE panel, which contains rich information regarding child, caregiver, parent, and household characteristics. By doing so, we can investigate a comprehensive set of potential factors associated with a child's ability to delay gratification as the first step for understanding the skill formation process of young children. In addition, we can account for individual heterogeneity by incorporating household consumption into the estimation of the caregiver's long-run discount factor and time-consistent parameter because the RIECE panel data contain detailed disaggregate consumption.

Our main finding is that the child's ability to wait and the caregiver's long-run discount factor are significantly positively correlated. In other words, a patient caregiver tends to have a patient child. This relationship is robust with different measures of caregiver discount factor and a rich set of control variables, including time-consistency parameter, child, parent, caregiver, and household characteristics, as well as screen and sleep time. Also, this result is aligned with findings in Chowdhury et al. (2022) for Bangladesh, Falk et al. (2021) and Kosse and Pfeiffer (2012) for Germany, and Brenøe and Epper (2022) for Denmark. However, caregivers in those studies are parents, while only 28.6% of our main sample are. In that sense, our work contributes to the literature by showing that the relationship between child and caregiver time preferences exists even when the caregiver is not a biological parent, regardless of whether a parent lives at home. To the best of our knowledge, this paper is the first to investigate this relationship in heterogeneous households regarding whether a caregiver is a parent and whether a parent lives at home. Also, we find that the caregiver's time-consistency indicator does not significantly correlate to child time preferences. This is also a novel finding because other related studies did not distinguish between a long-run discount factor and a time-consistency parameter.[10] However, this finding of an insignificant

[10]Chowdhury et al. (2022) used the total number of patient choices from a multiple price list and Kosse and Pfeiffer (2012) did not have a front-end delay time frame so that time-consistency could not be measured. On the other hand, Falk et al. (2021) used a survey question asking, "When it comes to financial decisions,

correlation between a caregiver time-consistency parameter and a child's ability to delay gratification confirms their results even though their estimation did not consider the time inconsistency feature of individual preferences.

Regarding child-related factors, we find that only the age and literacy ability of the child are significantly correlated to the child's ability to wait. In the case of age, our result is in line with Andreoni et al. (2019) and Bettinger and Slonim (2007). Interestingly, our study separately investigates math and literacy ability and finds that only literacy ability significantly correlates to a child's ability to wait. This finding is consistent with the review summary of Labrell et al. (2020) that language and social experiences support children's understanding of time through making time notion more explicit. However, this result contradicts previous evidence of Bettinger and Slonim (2007) and Chowdhury et al. (2022): Bettinger and Slonim (2007) found a positive correlation between child's math ability and patience. While Chowdhury et al. (2022) found a negative correlation between cognitive ability (a composite measure of full-scale IQ) and time preferences in children. Regarding caregiver and household characteristics, we do not find any significant correlation to the child's ability to wait. This result is aligned with Chowdhury et al. (2022) and Bettinger and Slonim (2007).

Moreover, we find no significant correlation between screen time (for television and the internet) and a child's ability to wait. This may sound a bit surprising as some evidence suggested the effect of early screen exposure on attention problems in children (Christakis et al., 2004), for instance. The possible explanation might be that we could not assess the content consumed during the screen time. Alternatively, it might be possible that the effect of screen time on the ability to delay gratification might be highly non-linear in the sense that only excessive screen time would have a significant adverse impact.

Another interesting finding is that the correlation between child time preferences and caregiver discount factor is significantly stronger with the caregiver's age. One possible explanation could be that the older caregiver might be able to spend more time together with

how do you assess your willingness to abstain from things today so that you will be able to afford more tomorrow?" (scale 0-10), and Brenøe and Epper (2022) elicited time preferences by questions regarding jobs of parents and children in different years.

the child. Unfortunately, this argument was not supported by the insignificant interaction term between the time preference measures of the caregiver and the amount of activity time spent together with the child. The activities covered in the survey might not be able to reflect the actual interaction between the caregiver and the child. Further research is needed to understand the role of adult-child interaction in preference formation. Further, all other heterogeneous effects of other supporting factors considered in this paper are not statistically significant. The insignificance suggests that time preference formation is far from understood, and more research is needed.

There are some limitations regarding measuring time preferences. First, this study's elicitation task for child time preference is a one-binary decision task. As a result, it is implausible to measure the discount factor and time-consistency parameter for the child, as in the case of the caregiver. It would be even more interesting to investigate the transmission of discount factor and time-consistency parameter separately. For future research, given the importance of early childhood development, an elicitation task that can measure the discount factor and time-consistency parameter should be developed and applied to young children.

Second, our paper has to assume a specific form for the utility function (log and linear utility functions) to estimate individual discount factors. However, it would be better to do that without arbitrarily assuming the functional form assumption. That would be possible if we could conduct a field experiment to elicit individual risk preferences, which could determine a utility functional form, as in the seminal paper by Andersen et al. (2008). We have to leave that to future research. Third, there might be measurement errors due to household consumption. Also, there might be other possible biases in the estimates due to omitted variables. However, we already have a much richer set of controls than previous studies.

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Table 2: Descriptive characteristics of variables regarding children

Variables	Main sample		Whole sample	
	Mean (SD)	N	Mean (SD)	N
	or Proportion	N	or Proportion	N
Decision				
Decision to wait	0.568	709	0.576	1078
Chose sweet as a reward	0.447	709	0.457	1062
Child				
Age (in months)	74.34 (11.63)	709	71.53 (14.51)	1078
Girl	47.2%	709	49.1%	1078
Math ability	0.02 (1.00)	709	0.03 (1.00)	1077
Literacy ability	0.01 (1.00)	709	0.03 (0.98)	1069
Only child	45.1%	709	43.4%	1078
First-born child	18.3%	709	18.1%	1078
Number of siblings	0.53 (0.62)	709	0.54 (0.62)	1078
Household				
Wealth (via factor analysis)	-0.03 (0.65)	709	-0.01 (0.66)	1078
Parent				
Parent as caregiver	28.6%	709	27.1%	1006
One parent	18.8%	709	18.0%	1078
Both parents	34.8%	709	37.3%	1078
Parents are divorced	19.2%	697	17.6%	1054
Time spending				
Screen time	0.03 (1.02)	709	-0.004 (0.99)	1075
Sleep time	-0.03 (1.00)	709	-0.003 (1.00)	1075
Activity time	-0.03 (1.01)	709	0.001 (1.01)	1076

Table 3: Descriptive characteristics of variables regarding caregivers

Variables	Main sample		Whole sample	
	Mean (SD)	N	Mean (SD)	N
	or Proportion	N	or Proportion	N
Decision				
Number of waiting choices in set 1	2.97 (2.40)	659	2.87 (2.39)	953
Estimated discount factor I	0.78 (0.21)	659	0.77 (0.21)	952
Estimated discount factor II	0.77 (0.21)	659	0.76 (0.22)	953
Estimated time-consistency parameter I	1.02 (0.31)	659	1.02 (0.31)	950
Estimated time-consistency parameter II	1.02 (0.31)	659	1.02 (0.31)	951
Caregiver				
Age (years)	50.91 (12.70)	658	50.68 (13.16)	963
Female	0.9	659	0.908	966
Education (years in school)	7.14 (3.69)	656	7.04 (3.58)	961
Elicitation-task-related				
Task payoff wanted	0.923	659	0.916	961
Caregiver played set 1 first	0.423	659	0.433	966
Caregiver's choice consistent	0.748	659	0.733	959

Table 4: Estimation results with caregiver discount factor I and time-consistency parameter I (calculated based on a log utility function with background consumption).

Outcome:	(I)	(II)	(III)	(IV)
Child's choice to wait	OLS	OLS	Probit	Probit
Caregiver discount factor I	0.274***	0.229**	0.273***	0.228**
	(0.092)	(0.100)	(0.088)	(0.095)
Time-consistency parameter I	0.025	-0.003	0.024	-0.004
	(0.069)	(0.072)	(0.066)	(0.068)
Child's age (in months)	0.004***	0.004***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Child's gender (1=girl)	0.037	0.044	0.037	0.045
	(0.039)	(0.038)	(0.038)	(0.037)
Household wealth, standardized	-0.036	-0.031	-0.035	-0.030
	(0.026)	(0.036)	(0.026)	(0.035)
Child's math ability, age-standardized	0.020	0.020	0.021	0.020
	(0.017)	(0.018)	(0.017)	(0.018)
Child's literacy ability, age-standardized	0.044**	0.047**	0.044**	0.047**
	(0.020)	(0.019)	(0.019)	(0.019)
Child's reward choice (1=sweet)	0.017	0.010	0.018	0.011
	(0.033)	(0.034)	(0.032)	(0.032)
Parent as main caregiver (1=yes)		0.007		0.008
		(0.071)		(0.070)
One parent lives in the HH (1=yes)		0.018		0.017
		(0.058)		(0.056)
Both parents live in the HH (1=yes)		0.002		0.002
		(0.056)		(0.055)
Observations	709	693	709	693
Clusters (schools)	106	106		

Notes: Caregiver discount factor I and time-consistency parameter I are calculated based on a log utility function with background household consumption. Standard errors, clustered on school level, are in parentheses. Columns III-IV report marginal effects from Probit regresssions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Specifications (I) and (II) include a constant while (II) and (IV) include time spending controls, siblings controls, caregiver's characteristics controls, elicitation-task-related controls and interviewer and day-of-week controls.

Table 5: Estimation results with caregiver discount factor II and time-consistency parameter II (calculated based on a linear utility function with background consumption).

Outcome:	(I)	(II)	(III)	(IV)
Child's choice to wait	OLS	OLS	Probit	Probit
Caregiver discount factor II	0.250***	0.203*	0.249***	0.202**
	(0.091)	(0.099)	(0.087)	(0.094)
Time-consistency parameter II	0.027	<-0.001	0.025	-0.002
	(0.069)	(0.072)	(0.066)	(0.068)
Child's age (in months)	0.004***	0.004***	0.004***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Child's gender (1=girl)	0.036	0.042	0.035	0.043
	(0.039)	(0.038)	(0.038)	(0.037)
Household wealth, standardized	-0.036	-0.032	-0.036	-0.030
	(0.026)	(0.036)	(0.026)	(0.035)
Child's math ability, age-standardized	0.020	0.020	0.021	0.020
	(0.017)	(0.018)	(0.017)	(0.018)
Child's literacy ability, age-standardized	0.044**	0.047**	0.044**	0.047**
	(0.020)	(0.019)	(0.019)	(0.018)
Child's reward choice (1=sweet)	0.017	0.010	0.017	0.010
	(0.033)	(0.034)	(0.032)	(0.032)
Parent as main caregiver (1=yes)		0.008		0.009
		(0.071)		(0.069)
One parent lives in the HH (1=yes)		0.017		0.017
		(0.058)		(0.056)
Both parents live in the HH (1=yes)		0.002		0.002
		(0.056)		(0.056)
Observations	709	693	709	693
Clusters (schools)	106	106		

Notes: Caregiver discount factor II and time-consistency parameter II are calculated based on a linear utility function without background household consumption. Standard errors, clustered on school level, are in parentheses. Columns III-IV report marginal effects from Probit regresssions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Specifications (I) and (II) include a constant while (II) and (IV) include time spending controls, siblings controls, caregiver's characteristics controls, elicitation-task-related controls and interviewer and day-of-week controls.

Table 6: Estimation results with caregiver's number of waiting choices.

Outcome: Child's choice to wait	(I) OLS	(II) OLS	(III) Probit	(IV) Probit
Caregiver's number of waiting choices	0.016**	0.017*	0.016**	0.017*
	(0.007)	(0.008)	(0.007)	(0.007)
Present-biased caregiver (1=yes)	0.063	0.037	0.063	0.037
	(0.044)	(0.045)	(0.043)	(0.044)
Future-biased caregiver (1=yes)	0.029	-0.004	0.028	-0.007
	(0.046)	(0.046)	(0.045)	(0.044)
Child's age (in months)	0.004***	0.004**	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Child's gender (1=girl)	0.036	0.045	0.035	0.045
	(0.038)	(0.038)	(0.038)	(0.037)
Household wealth, standardized	-0.037	-0.031	-0.036	-0.030
	(0.026)	(0.036)	(0.026)	(0.035)
Child's math ability, age-standardized	0.022	0.021	0.022	0.022
	(0.017)	(0.018)	(0.017)	(0.018)
Child's literacy ability, age-standardized	0.045**	0.048**	0.045**	0.047***
	(0.020)	(0.019)	(0.019)	(0.018)
Child's reward choice (1=sweet)	0.021	0.011	0.021	0.012
	(0.033)	(0.034)	(0.032)	(0.033)
Parent as main caregiver (1=yes)		0.010		0.010
		(0.072)		(0.070)
One parent lives in the HH (1=yes)		0.017		0.017
		(0.058)		(0.056)
Both parents live in the HH (1=yes)		¡0.001		0.001
		(0.055)		(0.054)
Sleep time, age-standardized (1=above median)		0.041		0.042
		(0.040)		(0.039)
Screen time, age-standardized (1=above median)		-0.006		-0.005
		(0.035)		(0.034)
Observations	709	693	709	693
Clusters (schools)	106	106		

Notes: Standard errors, clustered on school level, are in parentheses. Columns III-IV report marginal effects from Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Specifications (I) and (II) include a constant while (II) and (IV) include time spending controls, siblings controls, caregiver's characteristics controls, elicitation-task-related controls and interviewer and day-of-week controls.

Table 7: Heterogeneous effects.

	Discount factor I		Discount factor II		No. of waiting choices	
	(I) OLS	(II) Probit	(III) OLS	(IV) Probit	(V) OLS	(VI) Probit
One parent (d)	-0.054	-0.051	-0.067	-0.065	-0.001	-0.001
	(0.249)	(0.239)	(0.247)	(0.237)	(0.021)	(0.020)
Both parents (d)	0.305	0.308	0.274	0.277	0.034*	0.035**
	(0.205)	(0.198)	(0.203)	(0.195)	(0.017)	(0.017)
Parent as CG (d)	-0.075	-0.079	-0.081	-0.085	-0.003	-0.003
	(0.182)	(0.177)	(0.183)	(0.178)	(0.016)	(0.015)
Divorced (d)	-0.113	-0.117	-0.106	-0.109	-0.007	-0.007
	(0.185)	(0.175)	(0.182)	(0.172)	(0.018)	(0.017)
CG Age (years)	0.017***	0.017***	0.017***	0.017***	0.001**	0.001***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)
CG Female (d)	-0.444	-0.435	-0.430	-0.423	-0.034	-0.033
	(0.277)	(0.273)	(0.270)	(0.267)	(0.023)	(0.023)
CG Years of edu	-0.017	-0.018	-0.016	-0.017	-0.001	-0.001
	(0.021)	(0.021)	(0.022)	(0.021)	(0.002)	(0.002)
Same gender (d)	-0.191	-0.184	-0.216	-0.209	-0.011	-0.011
	(0.185)	(0.177)	(0.183)	(0.176)	(0.016)	(0.016)
Parenting style	0.038	0.048	0.025	0.035	0.006	0.007
	(0.117)	(0.113)	(0.114)	(0.110)	(0.010)	(0.010)
Age (months)	-0.001	$<$-0.001	$<$-0.001	$<$0.001	$<$0.001	$<$0.001
	(0.008)	(0.008)	(0.008)	(0.008)	($<$0.001)	($<$0.001)
Female (d)	-0.125	-0.116	-0.152	-0.144	-0.006	-0.006
	(0.190)	(0.183)	(0.189)	(0.182)	(0.017)	(0.016)
Math	-0.037	-0.034	-0.046	-0.043	$<$0.001	$<$0.001
	(0.090)	(0.088)	(0.089)	(0.087)	(0.008)	(0.008)
Literacy	0.052	0.056	0.050	0.054	0.005	0.005
	(0.094)	(0.090)	(0.093)	(0.089)	(0.008)	(0.008)
Only child (d)	-0.183	-0.183	-0.198	-0.197	-0.021	-0.021
	(0.148)	(0.141)	(0.146)	(0.139)	(0.014)	(0.013)
First-born (d)	0.045	0.040	0.053	0.047	0.002	0.001
	(0.247)	(0.240)	(0.248)	(0.241)	(0.021)	(0.021)
No. of siblings	-0.032	-0.029	-0.033	-0.030	0.003	0.004
	(0.137)	(0.133)	(0.134)	(0.129)	(0.012)	(0.012)
Screen time (d)	-0.059	-0.058	-0.043	-0.041	-0.012	-0.012
	(0.166)	(0.161)	(0.160)	(0.155)	(0.014)	(0.014)
Sleep time (d)	-0.214	-0.208	-0.210	-0.204	-0.014	-0.014
	(0.180)	(0.174)	(0.176)	(0.170)	(0.016)	(0.015)
Activity time (d)	0.092	0.080	0.084	0.073	0.016	0.015
	(0.193)	(0.186)	(0.189)	(0.181)	(0.016)	(0.015)
Wealth	-0.101	-0.104	-0.116	-0.118	-0.001	-0.001
	(0.122)	(0.115)	(0.120)	(0.113)	(0.011)	(0.011)

Notes: Standard errors, clustered on the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (d) specifies a dummy variable. Each estimate is an estimation coefficient of an interaction term between the corresponding variable and discount factor I (I-II), discount factor II (III-IV), or the number of waiting choices (V-VI). All specifications include time spending controls, siblings controls, caregiver's characteristics controls, elicitation-task-related controls and interviewer and day-of-week controls.

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