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Abstract

Most economic models assume that time preferences are stable over time, but the evidence on their long-term stability is lacking. We study whether and how time preferences change over the life cycle, exploiting representative long-term panel data. We provide new evidence that discount rates decrease with age and the decline is remarkably linear over the life cycle. Decreasing discounting helps a canonical life-cycle model to explain the household saving puzzles of undersaving when young and oversaving after retirement. Relative to the model with constant discounting, the model's fit to consumption and asset data profiles improves by 40% and 30%, respectively.

JEL-Codes: D150, D910, E210, J100.

Keywords: time preferences, preference stability, discount rates, household saving puzzles.

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1 Introduction

A key assumption of life-cycle models is that time preferences—crucial primitives that govern intertemporal trade-offs—are stable over the life cycle. Since these models are a workhorse for modern economic analyses, the validity of this assumption has important implications for many of economic analyses about consumption-savings decisions and portfolio choices. This assumption is also a foundation for structural estimation of time preferences using consumption Euler equations.[1] However, it has been challenging to test whether and how time preferences change with age because there is a well-known identification problem; without data with a long time horizon, disentangling age effects from influences of period-specific and cohort-specific factors is impossible. This identification problem might explain why previous studies, all relying on short panel or cross-sectional data, find mixed results about the age pattern of time preferences.[2]

This paper studies whether and how time preferences change with age, exploiting novel long-term panel data from the Japanese Household Panel Survey (JHPS). The data consist of a representative sample of Japanese households surveyed since 2009. The JHPS provides key information about time preferences based on the standard hypothetical question of monetary discounting. One advantage of using this information is that answers to the question are convertible to discount rates, and thus the measure of time preferences is comparable across individuals over time. The unique feature of the data set compared to other nationally representative household surveys is that it asks the same question on time preferences to the same individuals annually for nine consecutive years, which provides rich time variation to disentangle age effects from cohort effects.

Even with the long panel data, there is an identification problem because age is a linear combination of birth and survey year, and thus we cannot control for these variables at the same time. There is also no strong reasoning to omit one of them a priori, as they all have a potential impact on measured time preferences. Age could affect time pref-

[1] E.g., Lawrance (1991) and Gourinchas and Parker (2002).

[2] Some studies find that discount rates are lower among older individuals (e.g., Green et al., 1994; Warner and Pleeter, 2001), whereas others find the opposite pattern (e.g., Chesson and Viscusi, 2000). There are also studies that find that middle-aged individuals are the most patient compared with the young and the elderly (e.g., Read and Read, 2004; Falk et al., 2018). Finally, several studies find no relationship between age and discount rates (e.g., Coller and Williams, 1999; Chao et al., 2009).

erences for biological reasons. Rogers (1994) argues that time preferences are associated with reproductive potential, which varies with age. Daly et al. (2009) provide evidence that time discounting is related both to biological measures such as heart rate variability and blood pressure and to psychological variables such as self-control. Green et al. (1994), Green et al. (1996), and Green et al. (1999) suggest that impulsivity and self-control may change with age and thereby affect the ability to delay gratification. Cohort effects might affect preferences through experiences (e.g., Alesina and Fuchs-Schündeln, 2007; Malmendier and Nagel, 2011). For example, experiencing economic dislocation after World War II, the rapid economic growth in the 1970s or one of the major earthquakes (e.g., the Great Hanshin earthquake in 1995) when young might affect time preferences (e.g., Kuralbayeva et al., 2019). In addition, the expected duration of life at birth or a given age varies by cohort and potentially affects time preferences (Falk et al., 2019).[3] Finally, calendar year effects might also influence measured time preferences because macroeconomic events such as recessions change expectations and thus elicited time preferences might be affected.

To address this identification problem, we use determinants of time preferences that depend on, but are not linearly related to, calendar years as substitutes for period effects, following Heckman and Robb (1985) and Dohmen et al. (2017). In the baseline specification, we control for the real interest rate to capture calendar year effects on time preferences. In addition, we include individual fixed effects to capture cohort effects, taking advantage of the long panel structure of the JHPS. The individual fixed effects are also able to capture all time-invariant observable and unobservable individual characteristics that potentially affect time preferences. Finally, we can separately identify age effects by age dummies.

Our main empirical finding is that discount rates decrease with age over the life cycle and the decline is remarkably linear for the whole range of age from 25 to 80. The decreasing age profile only emerges once we control for cohort effects. To quantify the age effect, we also conduct a fixed effects estimation with a continuous age variable and find that each additional year of age is associated with 1.3% decrease in the measured discount rates on average.

It is well-documented in the literature that there are household saving puzzles in a

[3]Note that the remaining duration of life at a particular age depends not only on age but also on cohort.

canonical life-cycle model; compared to the model, households in the data undersave in young ages (e.g., Bernheim, 1992; Skinner, 2007; Heimer et al., 2019) and do not dissave as much as predicted by the model in old ages (e.g., Hurd, 1987; Palumbo, 1999; Browning and Crossley, 2001). To illustrate the quantitative importance of our empirical finding, we consider a canonical life-cycle model calibrated to the Japanese economy using the JHPS data. We use the new estimation technique for the nonlinear income process developed by Arellano et al. (2017), which allows us to capture higher-order earnings risks for consumption insurance over the life cycle. The model with constant discount rates exhibits the saving puzzles as in the literature. We then show that imposing the decreasing discount rates in the same model significantly improves the prediction about consumption and savings behaviors in the data. Specifically, measured by sum of squared errors, the model's fit to the consumption and asset profiles increases by 39.8% and 30.2%, respectively. This result stems from the fact that young (old) agents are relatively less (more) patient than in the baseline model and thus they tend to frontload (backload) consumption.

Monetary discounting is the major tool for eliciting time preferences to this date mainly because of its simplicity (e.g., Dohmen et al., 2010; Ifcher and Zarghamee, 2011; Meier and Sprenger, 2015). We also rely on it, taking full advantage of the large sample size and long panel length of the data. The richness of our unique data set also allows us to address most of the key methodological challenges (Frederick et al. 2002; Cohen et al. 2020), which are often neglected in empirical papers eliciting time preferences. First, liquidity needs could be age-dependent and thus driving the decreasing age effects. To address this issue, we use the detailed data on household wealth and control for liquidity needs, but the results hardly change. We also identify hand-to-mouth consumers and find similar age profiles of discounting for more and less liquidity-constrained samples. Second, an important assumption behind monetary discounting is that the monetary payment is consumed upon receipt rather than transferred across periods, which might not hold especially for non-liquidity-constrained households. However, this argument is unlikely a relevant concern for our sample given that the discounting patterns are quite similar for more and less liquidity-constrained samples. Third, monetary discounting might only reveal marginal costs of borrowing for each individual or knowledge about arbitrage opportunities rather than true time preferences. To address this concern, we estimate marginal costs of borrowing and a degree of financial literacy, and show that neither of them decreases with age, which means that these factors do not seem to be driving our result. Moreover, our measure of time preferences is statistically significantly related to the socioeconomic status and actual intertemporal behavior such as years of schooling, health status, savings and smoking. The predictive power of our measured discount rate lends credence to the fact that our measure is related to true time preferences.

Another key assumption behind elicitation of discount rates is that the underlying utility function is linear for small stakes outcomes, but estimated discount rates may be biased if this assumption does not hold (Andersen et al., 2008). To address this concern, we use the Preference Parameters Study (PPS), another individual-level panel data set representative for Japan that allows for a joint elicitation of time and risk preferences using a version of double multiple price listing. We first estimate the curvature of the utility function and adjust the estimation of discount rates. Using a five-year panel, we find a downward sloping age effect on the measured discount rates with adjusting for curvature of utility. The estimated coefficient is statistically significant and, reassuringly, comparable to the one in the main analysis where we assumed linear utility.

Our empirical findings are robust to various other specifications. First, our results are not sensitive to the specific choices of proxy for the calendar year such as inflation, GDP growth, and stock market returns. Also, the results hold when we use proxy variables for the cohort and include a full set of calendar year dummies. Second, our findings are robust to controlling for subjective assessments of the health status or socioeconomic characteristics such as education, income or financial wealth (Fisher, 1930; Becker and Mulligan, 1997). Finally, we find a similar linear negative relationship between age and discount rates for both genders.

Our first contribution is to provide new empirical evidence that discount rates decrease with age. In their seminal paper, Stigler and Becker (1977) argue that preferences are stable over time, while this view is later challenged by others (e.g., Simon, 1981; Loewenstein and Angner, 2003). The lack of longitudinal studies on individual time preferences has long been recognized in the literature (Frederick et al., 2002; Almlund et al., 2011). For example, Frederick et al. (2002) write that "no longitudinal studies have been conducted to permit any conclusions about the temporal stability of time preferences" (p.391). To the best of our knowledge, this problem still persists today. There are, however, several recent studies that analyze short-term stability of discount rates, using a hypothetical question or an incentivized experiment from two-year panel data in Seattle/Denver (Krupka and Stephens Jr, 2013), in Boston (Meier and Sprenger, 2015), and in rural Paraguay (Chuang and Schechter, 2015). This paper contributes to this literature by exploiting a novel representative long-term panel data set, which allows us to study how time preferences change over the life cycle, beyond short-term preference stability of a limited set of population.

Our second contribution is to demonstrate that decreasing discount rates are an effective tool to bring the predictions of a canonical life-cycle model closer to the empirical consumption-savings patterns. Several studies have proposed mechanisms to improve the predictions of the canonical model—our approach is complementary to these mechanisms. For example, to explain the puzzle of slow decumulation of wealth after retirement, the literature has proposed uncertainty about the life span (Davies, 1981), bequest motives (Hurd, 1987), uncertainty about medical expenses (Palumbo, 1999), and public care aversion (Ameriks et al., 2011). Groneck et al. (2016) and Heimer et al. (2019) show that using subjective, instead of objective, survival beliefs in a simple life-cycle model improves the model performance about agents' savings behaviors over the life cycle. The present paper shows that decreasing discounting is also a quantitatively important explanation for the household saving puzzles.

The rest of this paper is organized as follows. In Section 2, we describe the JHPS and explain our empirical strategy. Section 3 reports the result. Section 4 illustrates the quantitative importance of our result. In Section 5, we discuss the robustness of our findings. Section 6 concludes the paper.

2 Data and Empirical Strategy

2.1 Data

We use data from the Japan Household Panel Survey (JHPS), an individual-level panel data set representative for the Japanese population, between 2010 and 2018.[4] We select

[4]See Appendix A.1 for details of the data set. Table A.1 presents summary statistics of our sample population. The JHPS starts in 2009, but we use the data from 2010 because after that the question regarding

Table 1: Number of Times of Observation in the Sample

Number of times observed	Number of individuals	Fraction of total individuals (cumulative)
9	1,462	43.5%
8	233	50.5%
7	184	55.9%
6	207	62.1%
5	163	66.9%
4	230	73.8%
3	256	81.4%
2	321	91.0%
1	303	100.0%

individuals aged 25 to 80 and drop observations with missing answers to the question on time preferences.[5] This leaves us with 21,000 observations in the pooled sample and 2,333 individuals each year on average. Table 1 reports the number of observations and the number of times that individuals are observed in our sample. It shows that panel attrition is relatively small. In the data, two-thirds of the individuals were observed at least five times, and 44% of the participants (1,462 individuals) participated in all of the nine waves. The average number of years of observation is 6.25.

Our measure of time preferences is elicited directly from a hypothetical question of monetary discounting in the JHPS. Elicitation is done by a version of matching tasks; respondents are asked about, instead of receiving 10,000 Japanese yen (JPY) one month later, at least how much they would like to receive 13 months later.[6] A respondent is presented with possible options ranging from an amount of JPY 9,500 to JPY 14,000 (i.e., rate of return from -5% to 40%). From the answers to this question, we calculate an internal rate of return r for each respondent. Assuming continuously compounding discounting,

time preferences is identical.

[5]We restrict our attention to the age range for which there is a sufficient number of individuals.

[6]Using the yearly average currency exchange rate of 2018, JPY 10,000 amount to 90.56 U.S. dollars.

we then convert it to discount rate ρ as follows:[7]

$$\rho = 100 \times \log(1+r). \tag{1}$$

Monetary discounting is still one of the major tools to elicit time preferences (e.g., Dohmen et al., 2010; Ifcher and Zarghamee, 2011; Meier and Sprenger, 2015). Thanks to its methodological simplicity, the non-response rate to the hypothetical question is quite low at 1.9% of all observations. Hypothetical questions like the one we use are experimentally validated. Note that our hypothetical question is not incentivized. However, several studies compare outcomes of real and hypothetical rewards and conclude that there is no significant difference between preference measures revealed by hypothetical questions and those indicated by incentivized experiments (Madden et al., 2003; Bickel et al., 2009; Vischer et al., 2013; Falk et al., 2016; Ubfal, 2016; Brañas-Garza et al., 2020). Frederick et al. (2002) and Cohen et al. (2020) provide an extensive survey of studies for eliciting time preferences. They also discuss important assumptions for measuring discount rates with the monetary discounting method. We address most of these issues in Sections 3.2 and 5.

A number of studies document that time preferences elicited by monetary discounting are reliable predictors of actual intertemporal behavior, such as addiction (Kirby and Petry, 2004), savings decisions (Ashraf et al., 2006; Falk et al., 2018; Epper et al., 2020), and credit card borrowing (Meier and Sprenger, 2010).[8] Golsteyn et al. (2014) also find that adolescent measured time preferences predict school performance, health, labor supply, and lifetime income. Our measure of time preferences is also related to the actual socioeconomic status and intertemporal behavior of the individuals in the sample (Table 2). Specifically, the measured discount rate is negatively related to savings, years of schooling, and subjective health measures and positively to smoking frequency, but not

[7]With continuously compounding discounting, the standard discount function becomes

$$\lim_{n\to\infty}\left(1+\frac{\rho}{n}\right)^{-n} = e^{-\rho},$$

which gives equation (1).

[8]See also Chabris et al. (2008) for a review of an association of discounting with smoking, alcohol consumption, drug use, and gambling.

Table 2: Time Preference Correlates

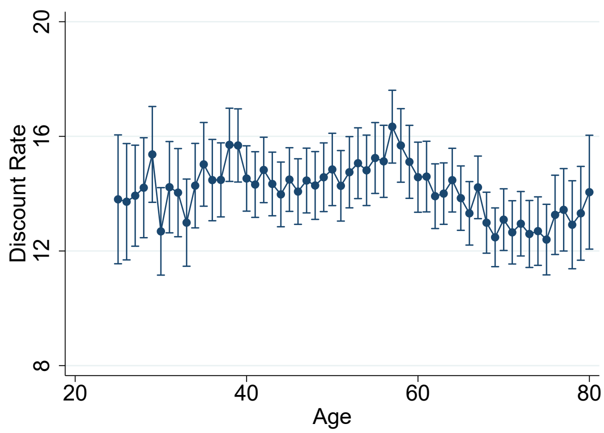
Dependent Variable	(1) Financial Wealth	(2) Years of Schooling	(3) Subjective Health	(4) Smoking Frequency	(5) Alcohol Consumption
Discount Rate	-0.080***	-0.005**	-0.002**	0.005***	0.000
	(0.021)	(0.002)	(0.001)	(0.001)	(0.001)
Education	YES	NO	YES	YES	YES
Age	YES	YES	YES	YES	YES
Gender	YES	YES	YES	YES	YES
Observations	19383	19487	20905	20938	20823
R^2	0.107	0.131	0.039	0.186	0.138

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. The table reports correlations between various socioeconomic status/intertemporal choices and our time preference measure. We estimate OLS models. Financial wealth is defined as the sum of "saving and deposit" and "securities" measured in hundred yen. The years of schooling are imputed from education category variables. Subjective health is given by a subjective assessment of the normal health condition. We assign a score ranging from 1 ("bad") to 5 ("good"). The smoking frequency variable is defined by the reported frequency (i.e., 1: never smoked, 2: used to smoke, 3: sometimes, or 4: every day). The alcohol consumption variable is defined by the reported drinking frequency (i.e., 1: never drink, 2: few times/month, 3: 1-2 times/week, or 4: 3+ times/week).

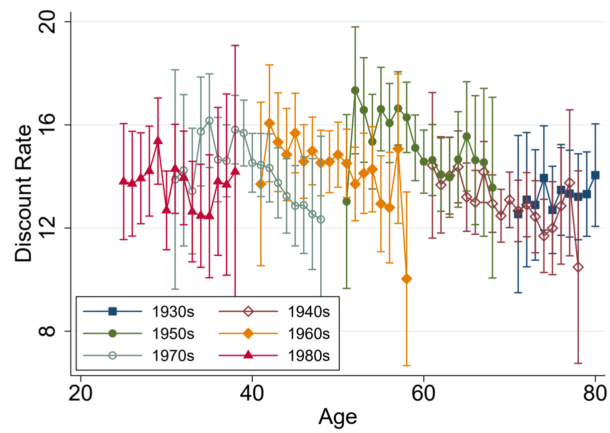
to alcoholic consumption.[9] These associations are all statistically significant. The predictive power of our measured discount rate lends credence to the fact that our measure is related to true time preferences.

There are several advantages of using the JHPS to study how time preferences change with age. First, while samples in previous studies are often small, highly restricted (e.g., to college students) and observed for a short period of time, we use nationally representative long-term panel data. To the best of our knowledge, the JHPS is the only representative data set that allows measuring discount rates annually for such a long time. Second, it asks the identical question on time preferences every year, so there is no potential bias caused by a modification of survey questions (e.g., amounts or time frames) or options individuals can choose from. Third, unlike hypothetical questions using Likert scales,

[9] Figure A.2 presents binned scatter plots for these relationships.



(A) Pooled Samples



(B) By Cohorts

Figure 1: Discount Rates across Age. The figure plots average measured discount rates against age for all individuals (Panel A) and separately for individuals born in 10-year bins (Panel B). The bars indicate 95% confidence intervals.

answers to the question in the JHPS are directly comparable across individuals over time without standardizing. Finally, estimates of discount rates would not be contaminated by a potential bias due to time-inconsistent preferences such as hyperbolic discounting whose degree is also potentially age-dependent, because the reference point of the questionnaire is one month later as opposed to today.

2.2 Empirical Strategy

We first present the relationship between measured discount rates and age in the raw data, pooling the data of all available years. Figure 1A plots average discount rates by age. In Figure 1B, we distinguish between different cohorts by plotting discount rates separately for individuals born in 10-year intervals (1930 to 1980 cohort). Figure 1A displays a slightly hump-shaped relationship between discount rates and age. However, once we consider differences across cohorts in Figure 1B, there emerges a downward-sloping relationship between discount rates and age within each cohort. These raw correlations already point at the importance of controlling for cohort effects when analyzing the relationship between age and time preferences.

In order to identify the effect of age on time preferences, we have to disentangle age

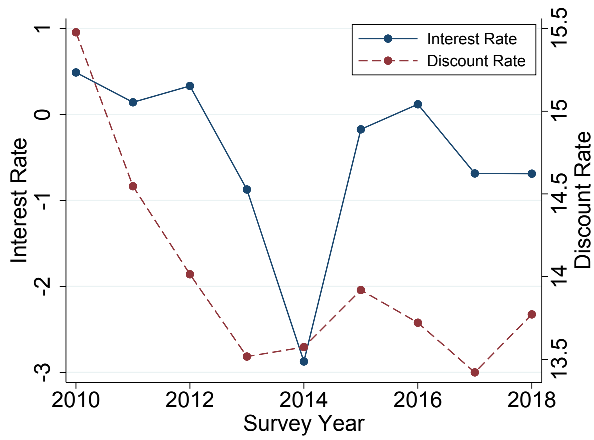


Figure 2: Interest Rate and Discount Rate. The figure plots measured discount rates (right axis) along with real interest rates (left axis). Real interest rates are constructed as inflation rates subtracted from the average interest rates posted on time deposits obtained from the Bank of Japan.

not only from cohort effects but also from period effects, because all three factors may affect measured discount rates. However, it is not possible to control for them simultaneously, as they are perfectly collinear. To tackle this issue, we follow the proxy variable approach in Heckman and Robb (1985) and Dohmen et al. (2017) and use a macroeconomic factor measured in a particular survey year as a substitute for calendar time.

The macroeconomic proxy variable helps resolve the identification problem if it meets the following conditions. First, it has to be related to measured time preferences. Second, it has to vary with calendar time but not in a linear fashion. As for the first condition, in light of the theory of intertemporal optimization, in our main specification, we choose real interest rates in the respective years as proxies for period effects. Figure 2 depicts the evolution of measured discount rates as well as the real interest rate between 2010 and 2018, the time period under consideration. It shows that the macro variable varies with calendar time, but not in a linear way, satisfying the second condition. In Section 5.1, we show that the results are not sensitive to the specific choices of proxy for the calendar year.

We estimate the following fixed effects model:

$$\rho_{it} = \alpha_0 + \alpha_i + \beta' age + \gamma macro_t + u_{it}. \tag{2}$$

The dependent variable ρ_{it} is the measured discount rate of individual i in period t calculated in equation (1). We control for individual fixed effects α_i, which capture, among others, cohort effects. In the baseline specification, we consider a full set of age dummies *age*. The variable $macro_t$ corresponds to the real interest rate measured in period t. The standard errors u_{it} are clustered at the individual level. Note that in this specification with individual fixed effects, selective non-response is not a relevant concern, because estimates of age effects are identified only from within-person changes.[10]

3 Discount Rates over the Life Cycle

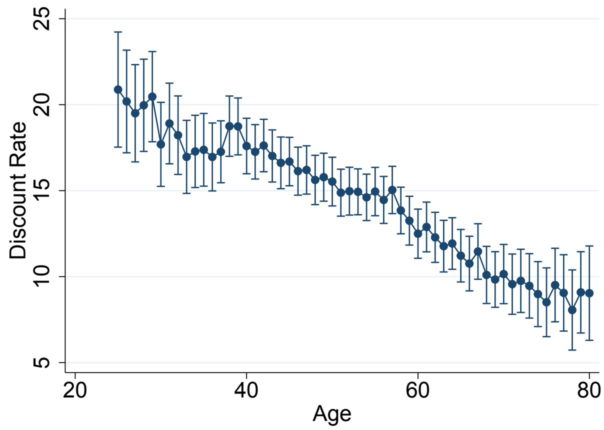
3.1 Main Empirical Analysis

Figure 3 shows the main result, namely the age effects from the fixed effects estimation (2) without and with controlling for period effects (Panels A and B, respectively). Both plots show that discount rates are decreasing with age and the decline is approximately linear. The introduction of the macro variable in Panel B makes the estimated age effects slightly flatter.

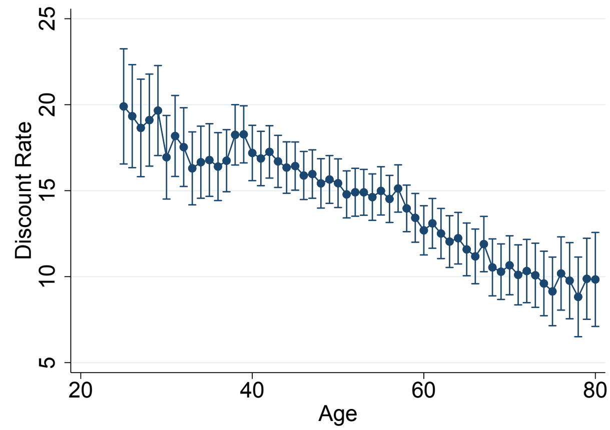
Given the approximately linear relationship between age and discount rates, to get a sense of the magnitude of age effects, we again estimate the fixed effects model (2) but replace age dummies with a continuous age variable. Table 3 presents the results. We introduce the independent variables successively: column (1) only includes age, column (2) adds individual fixed effects, and column (3) adds the macro variable (i.e., interest rate), which is our main specification. Throughout, the coefficient of age is negative and statistically significantly different from zero. The estimate in column (3) suggests that a one-year increase in age is associated with a decrease in the measured discount rate by 0.19 percentage points. Evaluated at the average discount rate in the sample of 14.14, this amounts to a 1.3% decrease.[11] The interest rate is positively related to the measured dis-

[10]The problem of selective non-response is that estimation results could be driven by non-random sample attrition. For example, because answering the survey question on time preferences is somewhat costly for participants, those who are more patient might tend to keep answering the question over years, which would result in a spurious negative relationship between age and discount rates. In Appendix A.2, we provide supportive evidence that selective non-response is generally not a concern in the JHPS irrespective of model specifications.

[11]The estimated average discount rate is larger than the one typically used in structural models, but



(A) Without Controlling for Period Effects



(B) With Controlling for Period Effects

Figure 3: Age Patterns Estimated with the Fixed Effects Model. The figure plots the values of age dummies in the individual fixed effects estimation with discount rates as the dependent variable with/without controlling for period effects. The bars indicate 95% confidence intervals.

count rate. In column (1), the negative relationship between the measured discount rate and age does indeed emerge, although the magnitude is much smaller at 0.03 percentage points, indicating almost a flat relationship between the measured discount rate and age. This suggests that it is paramount to account for cohort effects, as was already indicated in Figure 1B.

Our finding of diminishing discount rates over the life cycle is similar to empirical findings in experimental studies (Green et al., 1994; Tanaka et al., 2010) and field studies (Warner and Pleeter, 2001; Bishai, 2004; Andreoni et al., 2019). While investigating the mechanism behind the age profile is beyond the scope of the present paper, there are some existing theories consistent with our result.[12] Using an evolutionary biology approach, Rogers (1994) shows that age-dependent reproductive potential generates a decreasing

finding a high rate is not uncommon in the empirical literature. For example, Frederick et al. (2002) collect the estimated discount rates from many studies and argue that high discounting predominates, as most of the estimated discount factors are well below 1. Half of the 42 studies they list found discount rates above 30 (i.e., discount factors below 0.77; see their table 1). In Section 4, we investigate the quantitative implications of the high discount rate.

[12]However, the general pattern of age effects is not concluded in the theoretical literature. See e.g., Yaari (1965), Becker and Mulligan (1997) and Sozou and Seymour (2003) who predict different age profiles.

Table 3: Age Effects on Discount Rates

	(1)	(2)	(3)
Age	-0.030***	-0.219***	-0.187***
	(0.011)	(0.037)	(0.037)
Interest Rate			0.235***
			(0.072)
Individual FE	NO	YES	YES
Observations	21000	21000	21000
R^2	0.001	0.533	0.533

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. We estimate individual fixed effects models with discount rates as the dependent variable. Robust standard errors clustered at the individual level are reported in parentheses.

age profile for subjective discount rates among sexually matured adults. Introducing aggregate uncertainty whose effect differs across ages to the evolutionary approach, Robson and Samuelson (2009) present natural conditions under which the discount rate falls as a function of age. Halevy (2005) also shows that diminishing impatience would emerge for a decision maker with time-consistent preferences when lifetime is uncertain.

3.2 Curvature of Utility Function

A key assumption behind our measure of time preferences in equation (1) is that the utility function is linear for small stakes outcomes. However, estimated discount rates would be upward-biased if the actual utility function is concave (Andersen et al., 2008). Rabin (2000) shows that the linearity assumption is approximately true, while there are also studies that find substantial curvature in the utility function even for small stakes outcomes (e.g., Holt and Laury, 2002). Andreoni and Sprenger (2012) reject linearity of utility but also find that almost a third of subjects exhibit behavior that is fully consistent with linear preferences. Abdellaoui et al. (2013) compare utility under risk and utility over time and find that the former is concave, but the latter is linear for gains.

Unfortunately, there is no information for the curvature of the utility function available in the JHPS.[13] We thus turn to a different data set, the Preference Parameters Study (PPS), which allows a joint elicitation of time and risk preferences using a version of double multiple price listing (Andersen et al., 2008). The PPS is another individual-level panel data set representative for the Japanese population starting in 2003.[14] We use a relatively short panel of data between 2005 and 2009, when a hypothetical question of monetary discounting similar to the one in the JHPS is available. We select individuals aged 25 to 75 and drop observations with missing answers to the question on time preferences.[15] Finally, we exclude outliers from the sample based on the curvature-adjusted discount rate (top and bottom 1%; see below for details on the resulting range of annual discount rates considered in the analysis).[16]

Our measure of time preferences is again elicited from a hypothetical question of monetary discounting. Elicitation is done by the price list method: respondents are asked to choose whether they prefer receiving JPY 10,000 one month later or different amounts, ranging from JPY 9,500 to JPY 14,000, 13 months later (see Appendix A.4 for the exact question). From the answers to this question, we estimate a reservation payment F that makes the respondent indifferent between receiving P in a month and F in 13 months.

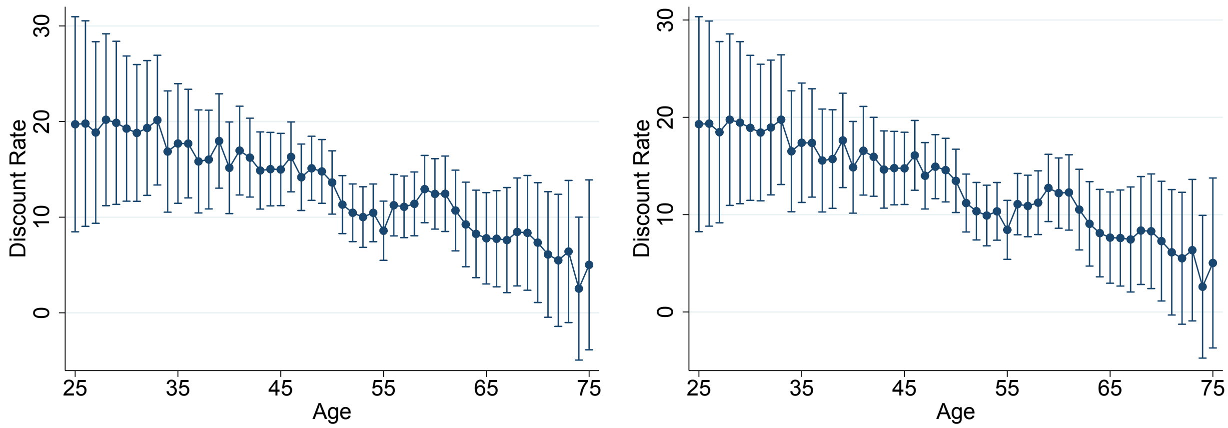
Before estimating the curvature of the utility function, using the PPS, we first confirm the results found in Section 3.1. In particular, we calculate the internal rate $1 + r = F/P$ for each subject and then convert it to a discount rate ρ by equation (1). Figure 4A shows that the profile for age effects estimated with the fixed effects model (2) is roughly linear and negatively sloped also in the PPS, similar to Figure 3B. Although standard errors are somewhat large due to a smaller sample size than in our main data set, the negative coefficient with a continuous age variable is still statistically significant at the 5% level (column 1 in Table 4). The magnitude of the age effect in the PPS is slightly larger but

[13]In Appendix B.1, we conduct further robustness checks using the JHPS. We first construct a variable that captures a degree of risk attitudes using a survey question and establish the validity of this risk attitude measure. We then add this measure as an additional control to the fixed effects estimation (2), following Meier and Sprenger (2015), and show that the age effects are virtually identical to our main result. Second, we adjust our measure of time preferences in equation (1) by considering background consumption. This adjustment generally makes the curvature of the utility function relatively a minor concern (Cohen et al., 2020). Reassuringly, we find a negative and significant age profile in this case too.

[14]See Appendix A.4 for details of the data set.

[15]We focus on individuals aged 75 or below because there are only 4 observations aged 76 and no observation aged 77 and above.

[16]Appendix C reports the results if we consider the full sample.



(A) Without Adjustment for Curvature

(B) With Adjustment for Curvature

Figure 4: Age Patterns and Curvature of Utility Function. The figure plots the values of age dummies in the individual fixed effects estimation controlling for the interest rate. The dependent variable is discount rates without/with adjusting for the curvature of the utility function. The bars indicate 95% confidence intervals.

comparable to the estimate in the JHPS: a one-year increase in age is associated with a decrease in the measured individual discount rate by 0.30 percentage points. Evaluated at the mean discount rate in the sample of 12.59, this corresponds to a 2.4 % decrease.

Next, we estimate the curvature of the utility function, using a hypothetical question of lottery purchases. In the survey, respondents are asked about their reservation price for purchasing a hypothetical lottery with a 50% chance of winning JPY 2,000 and a 50% chance of winning nothing. The PPS asks this hypothetical question between 2005 and 2008. Using the answers to it, we obtain

$$u(c) = (1-\pi)u(c-z) + \pi u(c-z+x), \tag{3}$$

where $u(\cdot)$ is the utility function, c is the level of consumption, π is the probability of winning, z is the reservation price, and x is the lottery prize.

We assume a CRRA utility function

$$u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}, \tag{4}$$

Table 4: Age Effects and Curvature of Utility

	(1)	(2)
Age	-0.297**	-0.288**
	(0.149)	(0.146)
Interest Rate	-0.159	-0.169
	(0.158)	(0.155)
Curvature Adjustment	NO	YES
Individual FE	YES	YES
Observations	10696	10696
R^2	0.626	0.626

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. We estimate individual fixed effects models. The dependent variable is the discount rate without/with adjusting for the curvature of utility. Robust standard errors clustered at the individual level are reported in parentheses.

where γ is the Arrow-Pratt measure of relative risk aversion. In this case, we can write[17]

$$\gamma = \frac{2\left(\pi x - z\right)c}{z^2 + \pi x\left(x - 2z\right)}. \tag{5}$$

The PPS reports average family non-durable expenditures per month, which we convert to per-adult equivalent expenditures. Since the winning prize is only JPY 2,000 (approximately 18.11 U.S. dollars), we use daily consumption for c, abstracting from intertemporal substitution.

Given the estimates of γ, we generalize equation (1) as follows:

$$\rho^* = -100 \times \log\left(\frac{c^{1-\gamma} - \left(c+P\right)^{1-\gamma}}{c^{1-\gamma} - \left(c+F\right)^{1-\gamma}}\right), \tag{6}$$

where (P, F) are hypothetical payments in the monetary discounting question. This equation nests equation (1) as a special case when the utility function is linear, i.e., $\gamma = 0$.

[17] See Appendix C for the derivation.

Here, to maximize the sample size and to get a stable estimate of discount rates, similar to Andersen et al. (2008), we assume a time-invariant utility function and only use contemporaneous consumption, which mitigates the issue of potential measurement error in consumption. In Appendix C, we discuss the underlying assumptions in more detail and show that relaxing them does not materially change the results.

We estimate γ by the average of all available years in the data. For consumption, we use annual per-adult equivalent non-durable expenditures. This results in values of ρ^* ranging from -15.47 to 43.18 with the average and median of 12.39 and 7.59, respectively, compared to 12.58 and 7.69 that are the average and median of ρ. The estimated discount rates with adjusting for the curvature of utility are thus lower than those with linear utility on average, consistent with Andersen et al. (2008).

Figure 4B plots the age effects estimated in the fixed effects model (2) with discount rates adjusted for the curvature of the utility function as the dependent variable. We find a negative relationship between age and discount rates in this case too. The age patterns are basically unchanged compared to those in Panel A where we assume linear preferences. Column (2) in Table 4 reports that the negative coefficient is statistically significant at the 5% level. Reassuringly, the estimated coefficient of -0.29 is close to the one in column (1).

4 Decreasing Discounting and Household Saving Puzzles

It is well-documented in the literature that there are household saving puzzles in a canonical life-cycle model; compared to the model, households in the data undersave in young ages (e.g., Bernheim, 1992; Skinner, 2007; Heimer et al., 2019) and do not dissave as much as predicted by the model in old ages (e.g., Hurd, 1987; Palumbo, 1999; Browning and Crossley, 2001). To illustrate the quantitative importance of our empirical finding, we consider a canonical life-cycle model calibrated to the Japanese economy using the JHPS data. We show that the baseline model with constant discount rates exhibits the saving puzzles as in the literature. We then demonstrate that imposing the decreasing discount rates significantly improves the model's prediction about consumption and savings behaviors, yielding a quantitatively important explanation for household saving puzzles.[18]

[18] In the same spirit, Groneck et al. (2016) and Heimer et al. (2019) show that using subjective, instead of objective, survival beliefs in a simple life-cycle model improves the model performance about agents'

4.1 A Canonical Life-Cycle Model

Consider a simple consumption-saving problem. Households have access to a single risk-free, one-period bond, and we assume a no-borrowing limit. The period-to-period budget constraint at age t is given by

$$c_t + a_{t+1} = y_t + (1+r)a_t, \tag{7}$$

where c is consumption, a is assets, y is labor income, and r is the constant return of assets.

The labor income is stochastic and follows the process

$$\log y_t = \kappa_t + \eta_t + \varepsilon_t, \tag{8}$$

where κ_t is a deterministic age profile, and η_t and ε_t are persistent and transitory components, respectively. All distributions are known to agents, and there is no aggregate uncertainty. From the retirement age that is exogenously given, agents receive pension.

The optimization problem is given by the Bellman equation

$$V_t(a_t, \eta_t, \varepsilon_t) = \max_{c_t, a_t \geq 0} \{u(c_t) + \beta s_t \mathbb{E}[V_{t+1}(a_{t+1}, \eta_{t+1}, \varepsilon_{t+1}) | \eta_t]\}$$

subject to equations (7-8), where β is the discount factor and s_t is the conditional survival probability at age t. Assume the CRRA utility function of the form (4). There is no utility from bequests. In the baseline model, the discount factor is assumed to be constant throughout the life.

4.2 Calibration

We assume that agents start the life at age 25, get retired at age 65 and can live until age 95. The conditional survival probability is taken from the life table. The real interest rate is set at 3.068%, the average value between 1975 and 2017 in Japan. The (after-tax) pension replacement rate is 61.7%.[19]

savings behaviors.

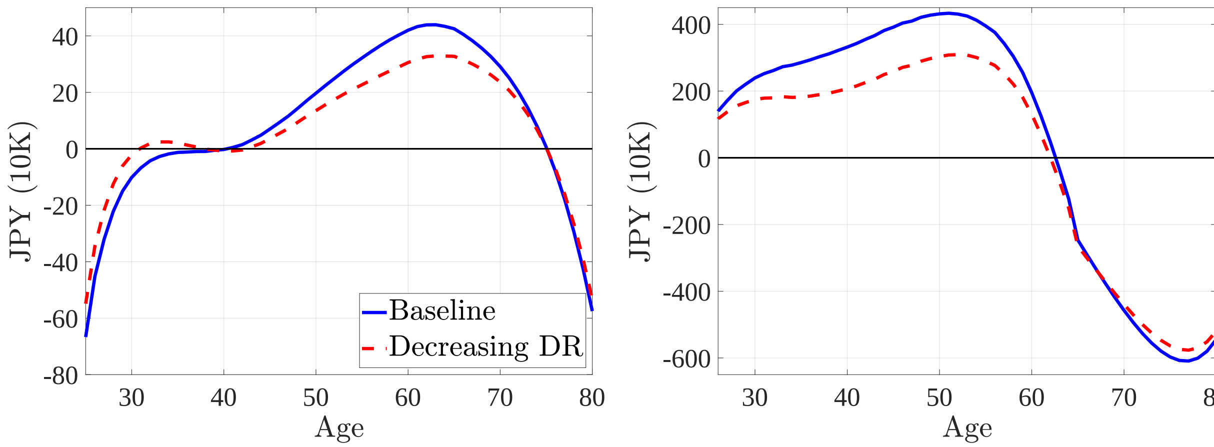
[19] The life table and the estimate of the replacement rate are taken from the Ministry of Health, Labour and Welfare of Japan. We obtain the interest rates from the World Bank database.

We estimate the labor income in equation (8) in two steps. First, we apply the quantile-based panel data method in Arellano et al. (2017) to estimate a nonparametric model. In the model, we assume absolutely continuous probability distributions for persistent and transitory components. Second, we specify the quantile functions obtained in the first step, simulate a large set of histories for the persistent and transitory component of earnings, and estimate a discrete Markov approximation. Estimating the nonlinear income process helps the model to fit the evolution of consumption insurance against persistent earnings shocks. We use data from the JHPS from 2010-2018, the same time period as in our empirical analysis, and focus on married couples, where the husband is aged between 25 and 64. We construct labor earnings as residuals from regressing log household labor earnings on a set of demographics.[20] Appendix D.1 presents more details of the estimation.

Finally, we calibrate the two preference parameters γ and β to match the life-cycle consumption profile from age 25-80, similar to Gourinchas and Parker (2002). We use data on consumption of nondurables and services. For housing service consumption, since rent information is only available for renters, we follow Blundell et al. (2016) to impute rent expenditures for home owners. We construct c as residuals from regressing log total consumption on the same set of demographics as for earnings. The calibrated parameter values in the baseline model are given by $\gamma = 1.873$ and $\beta = 0.961$.

Note that we calibrate the discount rate, rather than using the direct estimate from our empirical analysis in Section 3.1. This is because the *level* of discount rates depends on the empirical model and thus might be more sensitive to the model specification than the estimated *slope*. For the same reason, when experimenting decreasing discount rates, we impose a decrease in discount rates that is given by the estimated slope (1.3%) rather than by the estimated level (0.19 p.p.). In Appendix D.3, we also present the result when we use the estimated discount rate and only calibrate γ and the result when we impose the estimated level decrease in discount rates. The results with these alternative calibrations are qualitatively similar to the one below.

[20]Following Arellano et al. (2017), these demographic controls include education categories for both spouses, household size, the number of kids living in the household and a dummy for kids out of the household, a dummy for income recipients other than husband and wife, metropolitan areas, geographic area dummies, and survey year dummies.



(A) Consumption

(B) Asset Holdings

Figure 5: Predictions of the Canonical Life-Cycle Model. The figure plots the consumption (panel A) and asset holdings (panel B) profile over the life cycle for the baseline model with constant discount rates (blue solid) and the model with decreasing discount rates (red dashed), relative to the data. The data profile is smoothed by regressing on a fourth-order Hermite polynomial in age.

4.3 Effects of Decreasing Discount Rates

Figure 5 plots the deviation of consumption and asset holding in the model from the data over the life cycle. The asset profiles are constructed using income and consumption profiles together with the budget constraint. The life-cycle profiles (i.e., level) for these variables are found in Appendix D.2. We show that even the very simple canonical model above does a good job in replicating the overall hump-shaped profile of consumption and asset holdings (see Figure D.1).

Figure 5B shows, however, that the baseline model exhibits two well-known saving puzzles. Namely, the blue solid line turns from positive to negative at age 62, meaning that the model predicts higher asset holdings in young ages and lower asset holdings in old ages than in the data. This result is not very surprising given the fact that the model considered here is highly stylized.

We now demonstrate the quantitative importance of decreasing discount rates by imposing them in this simple life-cycle model. It is worth emphasizing that the purpose of this exercise is not to replicate the empirical pattern of whole consumption and asset profiles observed in the data, but to show that decreasing discounting leads the prediction of the canonical model in the right direction and significantly improves its fit to the data.[21]

For this purpose, we recalibrate the model assuming that discount rates decrease annually by 1.3%, the rate we found in the main empirical analysis in Section 3.1. To facilitate the comparison to the baseline model, we assume that discount rates are exogenously given and agents know how they change over time. The calibrated parameter values are given by $\gamma = 1.623$ and $\beta = 0.962$, where the latter is the average over the life. Compared to the baseline model, Figure 5A shows that the model with decreasing discount rates (red dashed line) predicts higher consumption when young and lower consumption when old (but not very old). This makes sense because young (old) agents are relatively less (more) patient than in the baseline model and thus they tend to frontload (backload) consumption.

The relatively small shift in flow consumption due to decreasing discount rates shown in Figure 5A has a large impact on the stock of savings as the effect accumulates over time. As Figure 5B shows, it results in lower asset holdings when young and higher asset holdings when old, making the asset profile flatter and closer to the data. The model's prediction about consumption and savings behaviors is significantly improved; measured by the sum of squared errors, the model's fit to the consumption and asset profiles increases by 39.8% and 30.2%, respectively. We thus conclude that decreasing discounting is a quantitatively important explanation for household saving puzzles.

5 Robustness and Methodological Assumptions

In this section, we show that our empirical results are robust to various alternative specifications and discuss important underlying assumptions of the monetary discounting method.

[21] A number of studies have proposed various fixes of the canonical model that potentially improve the model's prediction about saving behaviors, such as bequest motive (De Nardi, 2004) and uncertain medical expenditures (De Nardi et al., 2010).

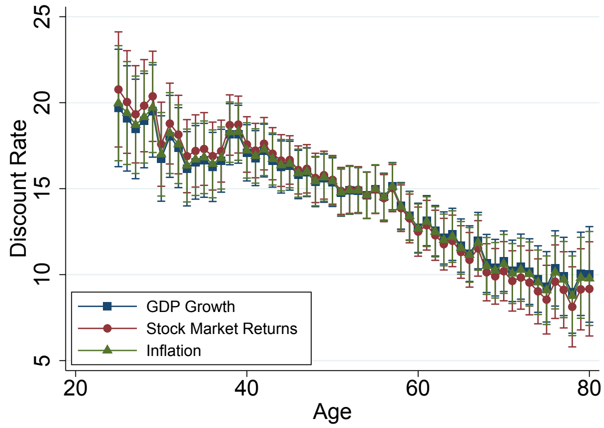


Figure 6: Age Patterns using Alternative Macro Variables. The figure plots the values of age dummies in the individual fixed effects estimation with discount rates as the dependent variable controlling for different macro variables. The bars indicate 95% confidence intervals.

5.1 Alternative Controls for Period Effects

In our baseline specification, we use real interest rates as substitute for period effects. To check the robustness, we instead use GDP growth (Hardardottir, 2017) which may capture general economic conditions and developments (e.g. medical advances that could have an impact on time preferences). We also consider stock market returns (i.e., Nikkei 225 return) or inflation as proxies for period effects. Figure 6 depicts the results when we use the alternative macroeconomic indicators. The estimates are robust. In all three cases, there is a negative slope, and the evolution of time preferences over the life cycle is hardly affected by the choice of proxy for the calendar year. In addition, we show in Appendix B.2 that our results are also robust to alternative approaches to resolve the identification issue: first, we use substitutes for cohort effects rather than survey years and second, we use group year dummies to capture period effects instead of substituting birth years or survey years. The estimates are robust in both specifications.

5.2 Socioeconomic Status

Socioeconomic status variables such as education, income, or financial wealth have long been thought to affect time preferences (Fisher, 1930; Hausman et al., 1979; Harrison et al., 2002; Falk et al., 2018). These socioeconomic variables as well as the subjective survival probability potentially vary with age, and thus there might be indirect effects of age on time preferences through them. In our baseline analysis, however, we did not control for them, because we are interested in capturing both direct and indirect effects of age on time preferences.

As the education level hardly varies over time by individual, we cannot control for the educational attainment in an individual fixed effects regression. Therefore, we group individuals into a low education sample (less than college) and a high education sample (college or more) and report the results separately for these groups in Table 5. Columns (1) and (2) refer to the low and high education groups, respectively. As they show, our results of the negative slope for age effects are robust to both education groups. The magnitude of the age effect is slightly larger for the low education group than for the high education counterpart.

To account for the possibility that income and/or financial wealth change with age, which could potentially have an impact on preferences, we control for these two factors in columns (3) and (4) of Table 5. To control for income, we take the log of the total household after-tax income (column 3). Financial wealth is defined as the sum of "saving and deposit" and "securities", observed separately in the data. We control for it in column (4). The estimates are robust in both specifications: the resulting coefficients for age are negative and statistically significant and also the magnitude of the effect barely changes.

Subjective survival probabilities could vary by age and could be correlated with time preferences. While we do not observe subjective survival probabilities, the data include a measure of the subjective health status, which is likely to be highly correlated with subjective survival probabilities. We control for the health status in column (5). Also in this specification, the estimate of the age effect remains stable.

Finally, column (7) shows that our estimates are robust when we include all these controls jointly as well as the wealth-to-income ratio, which we discuss below.[22]

[22]Note that these controls are measured contemporaneously. In Table B.2, we also present the results

Table 5: Controlling for Socioeconomic and Subjective Health Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	-0.209***	-0.188***	-0.199***	-0.182***	-0.187***	-0.206***	-0.209***
	(0.054)	(0.053)	(0.040)	(0.039)	(0.038)	(0.041)	(0.042)
Interest Rate	0.143	0.311***	0.210***	0.210***	0.233***	0.205***	0.207***
	(0.102)	(0.110)	(0.076)	(0.075)	(0.072)	(0.078)	(0.078)
Individual FE	YES	YES	YES	YES	YES	YES	YES
Log Income	NO	NO	YES	NO	NO	NO	YES
Financial Wealth	NO	NO	NO	YES	NO	NO	YES
Health Status	NO	NO	NO	NO	YES	NO	YES
Wealth to Income	NO	NO	NO	NO	NO	YES	YES
Education Sample	LOW	HIGH	ALL	ALL	ALL	ALL	ALL
Observations	11087	8400	18364	19341	20849	17603	17557
R^2	0.517	0.555	0.548	0.536	0.533	0.549	0.549

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. We estimate individual fixed effects models with discount rates as the dependent variable. Clustered standard errors at the individual level are reported in parentheses. The low education sample consists of individuals with less than a college degree, whereas the high education sample has a college degree or more. Log income is defined as the log of the total household after-tax income. Financial wealth is defined as the sum of "saving and deposit" and "securities". The Wealth to Income ratio is computed as financial wealth divided by the total household after-tax income. The health status is based on a subjective assessment of the own health status.

5.3 Liquidity

In the previous subsection, we controlled for financial wealth to allow for the possibility that time preferences are affected by wealth. However, the extent to which a household is liquidity-constrained could have an impact on our results because it may affect not only true time preferences but also measured time preferences. Since young households are more likely to be liquidity-constrained and tighter constraints make agents appear more impatient based on monetary discounting questions, our result of age effects could potentially be driven by liquidity needs.

To address this concern, we first construct a variable for the degree of household liquidity as financial wealth divided by disposable income as suggested by Kaplan et al. (2014). We include this variable as an additional control in Table 5, column (6). The age

when controls are measured in 2010, running pooled OLS regressions with cohort fixed effects. The result are very similar to those reported in Table 5.

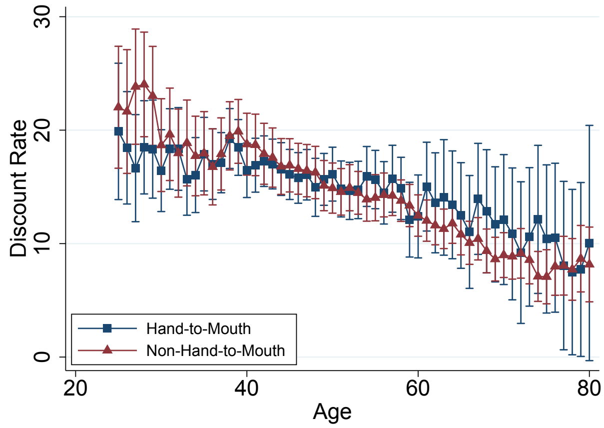


Figure 7: Age Patterns for Hand-to-Mouth and Non-Hand-to-Mouth individuals. The figure plots the values of age dummies in the individual fixed effects estimation separately for liquidity-constrained and unconstrained individuals. The bars indicate 95% confidence intervals.

coefficient remains negative and statistically significant.

Using the definition of hand-to-mouth households by Kaplan et al. (2014), we then split the sample in liquidity-constrained individuals (individuals whose financial wealth is less than or equal to half their annual earnings) and less constrained individuals (those with financial wealth larger than half their earnings) to check whether the relationship between age and time preferences is different for more and less liquidity-constrained individuals. Reassuringly, Figure 7 shows that there is a negative age slope for both groups. The age profile is slightly steeper for the non-hand-to-mouth individuals.[23] However, overall the age patterns are similar for the two sub-samples. Therefore, we conclude that our result of age effects is not driven by liquidity needs.

5.4 Consumption Flow versus Monetary Flow

One critique of the monetary discounting literature is that the question measures attitudes over earlier or later monetary payment. However, the relevant model is characterized by time-dated consumption. The underlying assumption to regard time-dated money as a

[23]The estimates for the hand-to-mouth sub-sample become less precise when age increases, reflecting the smaller number of liquidity-constrained individuals in this age group.

time-dated consumption is that the monetary payment is consumed in short order upon hypothetical receipt and thus considered as an increment of consumption in the same period. However, this assumption would not generally hold because money is transferable across periods. In our case, the amount in the hypothetical question in the JHPS is only JPY 10,000 (approximately 91 USD), which is 0.2% of the average income, so it would perhaps less likely trigger intertemporal transfers, which at least partly dampens the concern.

A strand of the literature critical of this framework instead uses real consumption events to measure time preferences such as effort task (e.g., Augenblick et al., 2015).[24] While Augenblick et al. (2015) find a considerably higher degree of present bias in effort task choices than in monetary choices, the estimates of long-run discounting are similar in both experiments.

In addition, the concern of intertemporal transfers should be more relevant for non-liquidity-constrained individuals. In contrast, we would expect liquidity-constrained individuals to consume their monetary payment immediately. Thus, the assumption of equivalence between consumption and monetary flows is more likely to hold for hand-to-mouth consumers. Figure 7 splits the sample into hand-to-mouth and non-hand-to-mouth individuals. The result suggests that the age patterns are not significantly different for the two subgroups, indicating that this may be less of a concern for our sample.

5.5 Intertemporal Arbitrage

There is a concern that monetary discounting might only reveal marginal costs of borrowing for each individual rather than true time preferences. In Section 2.1, we demonstrated the predictive power of our measure of time preferences for actual intertemporal behavior, which suggests that our measure is related to true time preferences, not just marginal costs of borrowing. Dohmen et al. (2010) provide direct evidence that most participants of their monetary discounting experiment are not engaging in arbitrage; only 37 percent of subjects thought about an interest rate during the experiment. Coller and Williams (1999)

[24]While this alternative approach does not suffer from the argument of intertemporal monetary transfers, there still remains measurement challenges. For example, even if consumption or effort task in an experiment is directly controlled, the subject might engage in offsetting behavior outside the experiment, which is a form of consumption smoothing. See Cohen et al. (2020) for more discussion.

show that once subjects are informed about the annual interest rates associated with each future payment, which is also the case for the question in the JHPS, providing information about available market rates in addition does not affect measured time preferences.

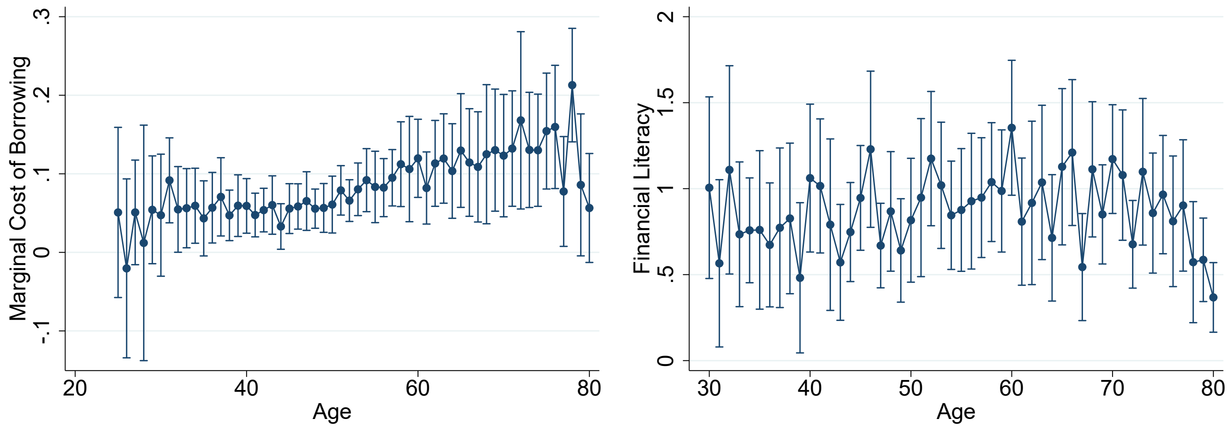
There are still some potentials that our findings are driven by intertemporal arbitrage rather than age effects. For example, if older individuals faced lower marginal costs of borrowing than younger ones, then the measured discount rates would decrease with age. Also, the same pattern would be observed, if they faced the same interest rate but older individuals were more likely to understand arbitrage opportunities.

To address the concern that interest rates faced by individuals might decrease with age, we investigate how costs of borrowing evolve over the life cycle, using panel information on mortgage loans and mortgage repayments.[25] Survey participants are asked for their annual sum of interest and amortization payments of their mortgages and the total current mortgage loan balance each year. Using this information, exploiting the panel dimension, and imposing the assumption that interest accrues annually, we are able to impute the individual borrowing rate.[26] Figure 8A plots the results of an individual fixed effects estimation regressing the computed borrowing rates on age dummies. The marginal costs of borrowing seem to be relatively stable between age 25 and 50 and are increasing afterwards. Thus, we do not find evidence that the marginal costs of borrowing are decreasing with age.

Next, we check whether a better understanding of arbitrage opportunities by older people could be driving our results. For this purpose, we construct a measure of financial

[25]It would be ideal if we could also compute borrowing rates of credit card loans, which are not available in our data set. However, credit card loans are not so common in Japan in the first place. For example, according to a survey by the Yu-cho Foundation conducted in 2019, among a random sample of 2,164 individuals aged 20 or above, 18% have ever held credit card or consumer loans, and only 6.4% held any of these loans at the time of the survey. See http://www.yu-cho-f.jp/wp-content/uploads/survey_report-6.pdf (in Japanese).

[26]To get consistent estimates, in addition we impose the following three restrictions: first, the annual mortgage payments must be larger or equal to the difference between the mortgage loan balance in two subsequent years. Second, we only use observations where the mortgage balance stays constant or decreases from one year to the other (an increase in the mortgage balance may indicate that a new mortgage is added by the individual, which would confound the computation). Finally, we exclude observations with interest rates larger than 50%. Based on this restriction we drop 57 outliers (3% of the sample). We also impose alternative thresholds, e.g., only dropping observations with borrowing rates larger than 80% or 100% and the results are robust to these alternative thresholds. The median of the computed interest rate is 5%.



(A) Marginal Costs of Borrowing

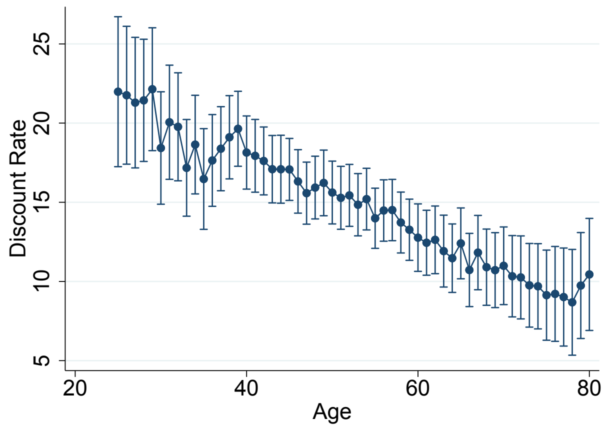
(B) Financial Literacy

Figure 8: Marginal Costs of Borrowing and Financial Literacy over the Life Cycle. Panel A plots the values of age dummies in a fixed effects estimation with a measure of the marginal costs of borrowing as the dependent variable. Panel B plots the values of age dummies in an OLS estimation with a measure of financial literacy as the dependent variable controlling for education and gender. The bars indicate 95% confidence intervals.

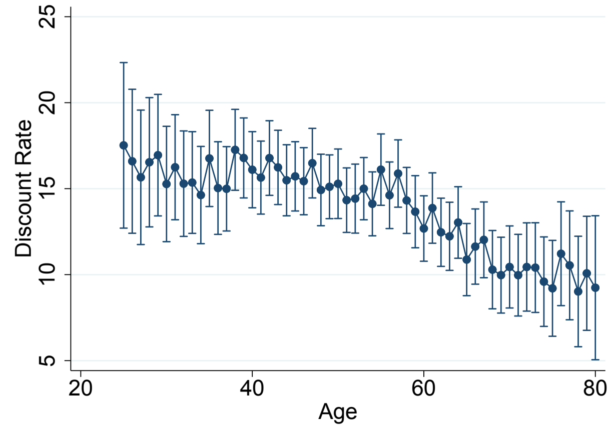
literacy using several questions in the JHPS asked in 2018.[27] We use the number of correct answers to these questions to construct a measure of financial literacy. Higher values of this variable thus indicate better financial literacy. We regress this measure on age dummies controlling for education and gender. As these questions are only available for one survey wave, we cannot include individual fixed effects. The estimates are plotted in Figure 8B. The results do not indicate a clear age pattern. In particular, the figure does not suggest that financial literacy is growing with age. We thus do not find evidence for the claim that intertemporal arbitrage opportunities change with age in a way such that

[27] The question asks: “Do you think that the following statement is true or false? (Circle one only) True - False - Do not know”

- “Buying a single company stock usually provides a safer return than a stock mutual fund.”
- “When interest rates go up, it is appropriate to invest in fixed interest rate assets and borrow variable interest rate loans.”
- “Suppose you had 100 thousand yen borrowings and the interest rate was 20 percent per year. If you do not make any repayments and leave the borrowings to grow, it is after 5 years that your amount of borrowings increases to 200 thousand yen.”



(A) Males



(B) Females

Figure 9: Age Patterns by Gender. The figure plots the values of age dummies in the individual fixed effects estimation with discount rates as the dependent variable controlling for the interest rate separately for males and females. The bars indicate 95% confidence intervals.

they could be driving our results.

5.6 Gender

Our results are robust to both genders. To see this, we estimate the fixed effects model (2) separately for males and females. Figure 9 plots the age dummies from this estimation. It shows that the estimated discount rates are roughly linearly decreasing with age, as in the baseline model. The slope of age effects is slightly steeper for males than for females, and females have somewhat lower discount rates (except for the very old).

5.7 OLS Estimation

In the baseline model, we estimate the fixed effects model (2), exploiting the long-term panel structure of the JHPS. We also estimate an OLS model with a full set of cohort dummies. In this case, estimates of age effects are identified not only from within-person changes but also from differences across individuals that the individual fixed effects previously controlled for. Figure 10 shows that the results are similar to our main findings

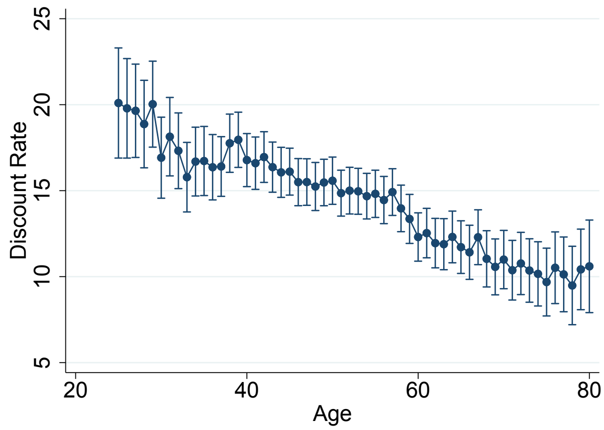


Figure 10: OLS Estimation. The figure plots the values of age dummies with discount rates as the dependent variable controlling for the interest rate and a full set of cohort dummies. The bars indicate 95% confidence intervals.

with this specification.

6 Conclusions

In this paper, we exploit representative long-term panel data in Japan and estimate age patterns of discount rates. We find that discount rates decrease with age and that the decline is remarkably linear over the life cycle. We show that decreasing discounting is a quantitatively important explanation for household saving puzzles in a canonical life-cycle model.

Our results are relevant for studies in household finance because time preferences are key economic primitives that govern intertemporal trade-offs. Our results may also be of interest for policymakers. For example, if a lower discount rate is associated with a higher saving rate, population aging may entail an increase in aggregate household savings. Exploring such implications of our empirical findings is future work.

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Time Preferences over the Life Cycle

Internet Appendix

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Hitoshi Tsujiyama   Midori Wakabayashi

Contents

A Data

A.1 Japan Household Panel Survey: General Information

The Japan Household Panel Survey (JHPS) is an individual-level panel data set representative for the Japanese population, starting in 2009.[1] The sample is stratified according to geographical area and city size. Self-administered paper questionnaires are delivered to and collected from the houses of participants. Table A.1 presents summary statistics of our sample population.[2]

We use the data from 2010 because since then the question regarding time preferences is identical. We select individuals aged 25 to 80 and drop observations with missing answers to the question on time preferences. All amounts are adjusted to 2015 JPY using the CPI.

Our measure of time preferences is elicited from a monetary discounting hypothetical question in the JHPS. Since 2010, participants of the survey were asked the same question annually to elicit their discount rates: "Instead of receiving 10 thousand yen one month later, at least how much would you like to receive 13 months later? Please choose one option from the following options 1-8":[3]

Option	Amount	Annual interest
1	9,500 yen	-5%
2	10,000 yen	0%
3	10,200 yen	2%
4	10,400 yen	4%
5	10,600 yen	6%
6	11,000 yen	10%
7	12,000 yen	20%
8	14,000 yen	40%

[1] https://www.pdrc.keio.ac.jp/en/paneldata/datasets/jhpskhps/

[2] The education shares in our sample compare to the educational attainment of the Japanese population aged 25 to 79 according to the last population census in 2010 as follows: 14% graduated from a junior high school, 41% from a high school, 13% from a junior college, 19% from either four-year university or graduate school and there were 13% with unknown education status. In the JHPS sample, 7% did not report their education attainment.

[3] Using the yearly average currency exchange rate of 2018, 10 thousand yen amount to 90.56 U.S. dollars.

Table A.1: Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Discount rate	14.14	12.48	-5.13	33.65
Age	53.89	14.67	25.00	80.00
Male	0.50	0.50	0.00	1.00
Educ: junior high school	0.07	0.26	0.00	1.00
Educ: high school	0.46	0.50	0.00	1.00
Educ: junior college	0.13	0.34	0.00	1.00
Educ: four-year univeristy	0.25	0.43	0.00	1.00
Educ: graduate school	0.02	0.14	0.00	1.00
After tax income (JPY 10,000, in 2015)	504	342	0	9999
Financial wealth (JPY 10,000, in 2015)	1134	2107	0	58151
Wealth to income ratio	2.90	7.52	0.00	375.00

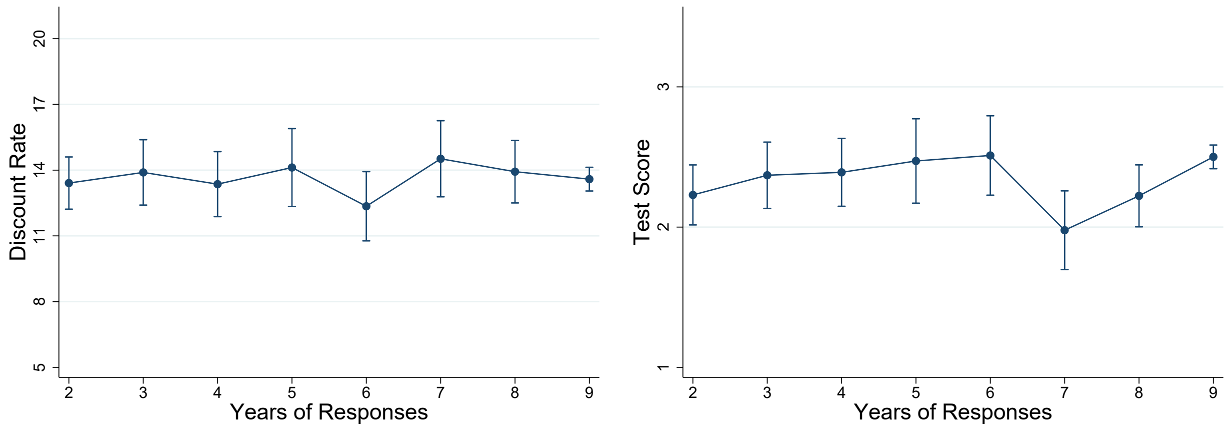
From the answers to this question, we calculate an internal rate of return r that is used in equation (1).

There are few observations who choose the first option (0.003%), which is difficult to be rationalized. We did not exclude these samples, but excluding them does not change our results.

A.2 Selective Non-Response

As discussed in Section 2.2, for our main specification with individual fixed effects, selective non-response is not a relevant concern, because estimates of age effects are identified only from within-person changes. In this section, we argue that irrespective of model specifications it is generally unlikely that selective non-response drives the negative relationship between age and discount rates.

First, because answering the survey question is somewhat costly for participants, one might imagine that those who are more patient tend to keep answering the question over years, which would result in a spurious negative relationship between age and discount rates. To address this issue, Figure A.1A plots the average measured discount rates against how many years an individual responds to the survey question for the relevant sample for the fixed effects estimation (ranging from 2 to 9 years). It shows that the sam-



(A) Years of Responses and Discount Rates

(B) Years of Responses and Test Scores

Figure A.1: Selective Non-Response. Panel A plots the average measured discount rates against how many years an individual responds to the survey question. Panel B plots the average syllogism test scores against how many years an individual responds to the survey question. The bars indicate 95% confidence intervals.

ples who respond more often are not statistically different from those who respond less often in terms of their patience.

Second, one might think that those who keep answering the question over time are cognitively more abled. Because cognitively more abled individuals tend to be more patient (Dohmen et al., 2010), this would again result in a spurious negative relationship between age and discount rates. To address this indirect attrition problem, we use five syllogism questions in the JHPS that test individual logical abilities. In each question, participants are asked to choose one of five options that can be reached from premises presented.[4] There is an explicit instruction that participants should answer by themselves and cannot spend more than 1 minute for each question. We use the test scores ranging from 0-5 as the measure of individual logical ability. Figure A.1B plots the average test scores against how many years an individual responds to the survey question. It shows that the samples who respond more often are not statistically different from those who respond less often in terms of their logical abilities.

[4]See Shikishima et al. (2011, p.92) for an example of the question.

A.3 Correlates of Time Preferences

In Figure A.2, we show binned scatter plots on the correlations between various socioeconomic status variables/intertemporal choices and our time preference measure, controlling for education, age and gender. We present graphs for those variables where we found a significant correlation in Table 2. While we use 40 bins in Figure A.2, the results are very robust to changes in the number of bins. The graphs are in line with the correlations reported in Table 2.

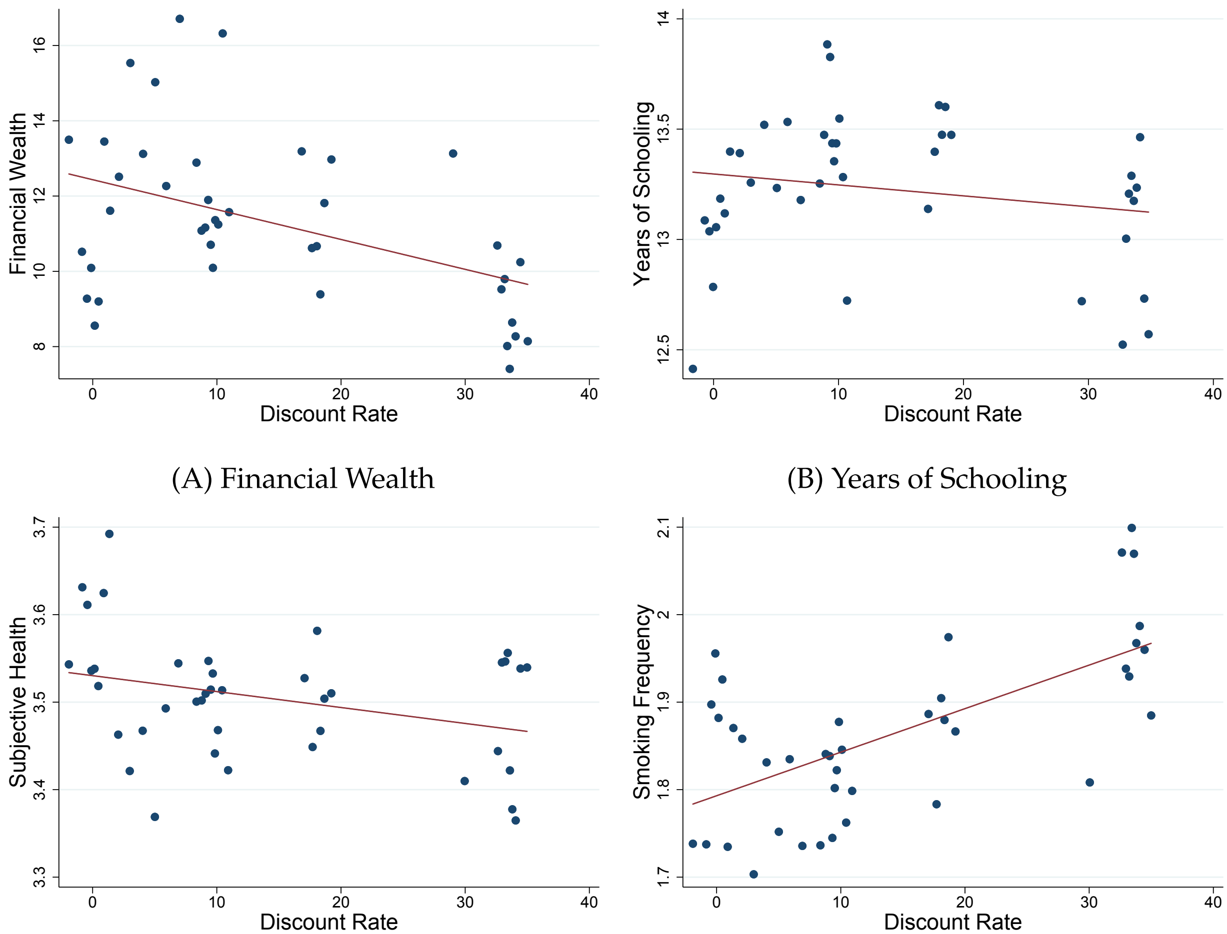
A.4 Preference Parameters Study: General Information

The Preference Parameters Study (PPS) is an individual-level panel data set representative for the Japanese population, starting in 2003.[5] Similar to the JHPS, the sample is stratified according to geographical area and city size. Self-administered paper questionnaires are delivered to and collected from the houses of participants.

We use the data between 2005 and 2009, when a question regarding time preferences similar to the one in the JHPS is available. On average, 3,900 individuals were interviewed annually. We select individuals aged 25 to 75 and drop observations with missing answers to the question on time preferences.

Elicitation of time preferences is based on a choice-based price list method. From 2005 to 2009, participants of the survey were asked the same question annually to elicit their discount rates: "Let's assume you have two options to receive some money. You may choose Option 'A', to receive JPY 10,000 a month from today; or Option 'B', to receive a different amount 13 months from today. Compare the amounts and timing in Option 'A' with Option 'B' and indicate which amount you would prefer to receive for all 8 choices."

[5] https://www.iser.osaka-u.ac.jp/survey_data/eng_panelsummary.html



(A) Financial Wealth

(B) Years of Schooling

(C) Subjective Health

(D) Smoking Frequency

Figure A.2: Time Preference Correlates. The figure reports correlations between various socioeconomic status/intertemporal choices and our time preference measure. We present binned scatter plots controlling for education (excluded in Panel B), age and gender (as in Table 2). Financial wealth is defined as the sum of "saving and deposit" and "securities" measured in hundred yen. The years of schooling are imputed from education category variables. Subjective health is given by a subjective assessment of the normal health condition. The score ranges from 1 ("bad") to 5 ("good"). The smoking frequency variable is defined by the reported frequency (i.e., 1: never smoked, 2: used to smoke, 3: sometimes, or 4: every day).

Option A Receiving a month from today	or	**Option B** Receiving 13 months from today	Includes An Annual Interest Rate Of:
10,000 yen		9,500 yen	-5%
10,000 yen		10,000 yen	0%
10,000 yen		10,200 yen	2%
10,000 yen		10,400 yen	4%
10,000 yen		10,600 yen	6%
10,000 yen		11,000 yen	10%
10,000 yen		12,000 yen	20%
10,000 yen		14,000 yen	40%

A respondent is asked to choose one of the two options. The reservation future payment (F) should lie in the interval between the two values where the respondent switches from Option A in one row to Option B in the next row. We define the reservation payment as the midpoint of the two values. Respondents who switch more than once are dropped. When a respondent chooses one option throughout, we assign an extrapolated value (i.e., 10% lower/higher amount than the lowest/highest option). We conduct robustness checks with respect to these values, but the results are materially unchanged.

To estimate the curvature of utility function, we use a hypothetical question of lottery purchases. From 2005 to 2008, participants of the survey were asked: "Let's assume there is a lottery with a 50% chance of winning 2,000 yen and a 50% chance of winning nothing. If the lottery ticket is sold for 200 yen, would you purchase a ticket?" If the answer to this question is *yes*, then the respondent is asked: "What is the most you would pay to purchase the lottery ticket mentioned in [the previous question]?" The possible options are to purchase if the price is less than (300, 400, 600, 1000, 2000) yen or to purchase even if the price is more than 2000 yen. If the answer to the first question is *no*, then the respondent is asked: "If the price of the lottery ticket was lowered, would you purchase it if . . . ?" The possible options are the price less than (190, 150, 100, 50) yen, the price of 1 yen, or "Wouldn't purchase even if the price is 1 yen."

From the answers to these questions, we obtain an estimate of the reservation price z, which is used to estimate γ in equation (5).

The PPS asks average family non-durable expenditures per month. To obtain per-adult equivalent expenditures, we divide the amount by the square root of the household size.

B Robustness for Section 3.1

B.1 Linearity Utility Assumption in the JHPS

A key assumption behind our measure of time preferences in equation (1) is that the utility function is linear for small stakes outcomes. However, estimated discount rates would be upward-biased if the actual utility function is concave (Andersen et al., 2008). Unfortunately, there is no information for the curvature of utility function available in the JHPS (our main data set). To address this concern, in the main text, we conduct a supplemental analysis of a joint elicitation of time and risk preferences using the PPS. Since the true utility function is never observed, however, we had to make a functional form assumption about the utility function.

In this section, we conduct additional robustness checks using the JHPS. First, we construct a variable that captures a degree of risk attitudes using a survey question. In the JHPS, participants are asked the following question: "When you go out to a place you have never been to before with your family or friends, what percentage of chance of rain makes you decide to take an umbrella?". We first construct a risk attitude measure (i.e, willingness to take risks) from this question. Specifically, we directly use answers to this question that are continuous from 0-100 (i.e., x% or higher), and for those who choose "I always take a folding umbrella", we assign 0. We use the resulting numbers as our measure of risk attitudes.

To establish the validity of this risk attitude measure, in Table B.1, we show that this risk measure is positively and statistically significantly related to the share of risky assets in total financial assets (columns 1 and 2) and risky behaviors such as smoking and alcohol consumption (columns 3 and 4), controlling for age and education. The share of risky assets is defined by securities divided by total financial assets. We also control for total financial assets in column (2), taking into account the possibility that individuals' absolute risk aversion is not necessarily constant. The smoking variable is defined by the smoking frequency (i.e., 1: never smoked, 2: used to smoke, 3: sometimes, or 4: every day). The alcohol consumption variable is defined by the drinking frequency (i.e., 1:

Table B.1: Risk Preference Correlates

Dependent Variable	(1) Share of Risky Assets	(2) Share of Risky Assets	(3) Smoking Frequency	(4) Alcohol Consumption
Risk Attitudes	0.014**	0.014**	0.004***	0.002***
	(0.007)	(0.007)	(0.000)	(0.000)
Education	YES	YES	YES	YES
Gender	YES	YES	YES	YES
Age	YES	YES	YES	YES
Total Financial Assets	NO	YES	NO	NO
Observations	15992	15992	22159	22035
R^2	0.053	0.104	0.192	0.138

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. The table reports correlations between various measures of risky behavior and our risk attitude measure. We estimate OLS models.

never drink, 2: few times/month, 3: 1-2 times/week, or 4: 3+ times/week). These results make us confident that the answers to the question above provide a good measure for risk attitudes.

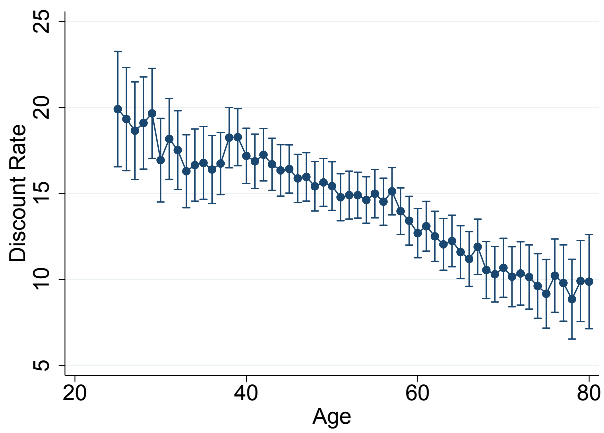
We then add this risk attitude measure as an additional control to the fixed effects estimation (2), as in Meier and Sprenger (2015). Figure B.1A shows that the age effects are virtually identical to our main result in Figure 3B.

Second, we adjust our measure of time preferences in equation (1) by considering background consumption. If the underlying utility function is strictly concave and background consumption is much larger than small stakes outcomes, the utility function becomes approximately locally linear. Therefore, this adjustment makes the curvature of utility function relatively a minor concern (Cohen et al., 2020). With background consumption c, we have

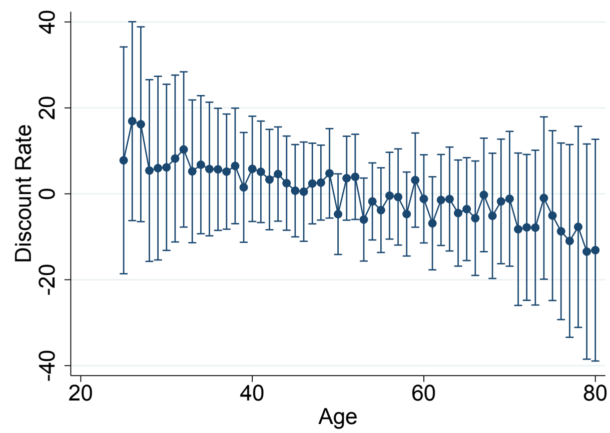
$$\rho = 100 \times \log\left(\frac{c_{t+1} + F}{c_t + P}\right).$$

We use per-adult annual equivalent consumption.

Figure B.1B plots the age effects estimated in the fixed effects model (2). Considering



(A) Controlling for Risk Attitudes



(B) Adjusting for Background Consumption

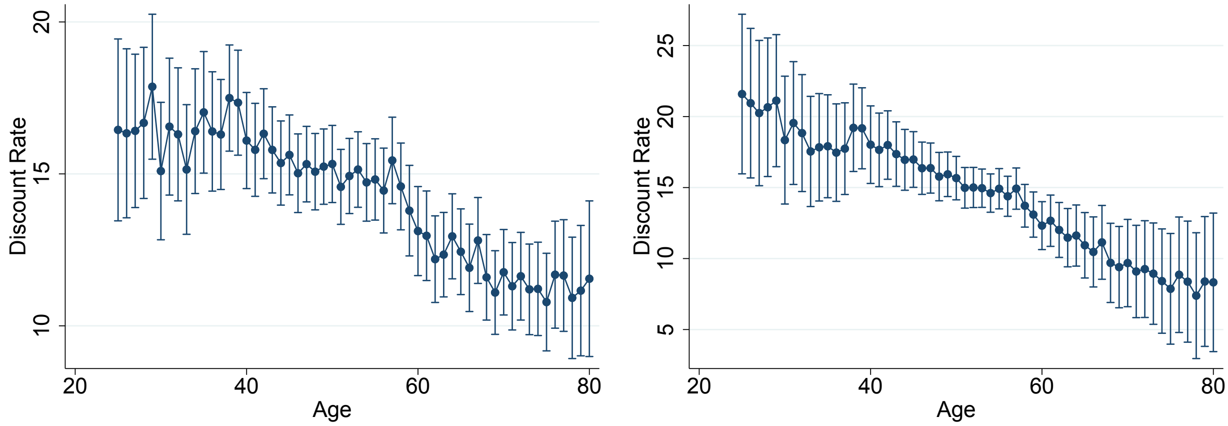
Figure B.1: Robustness Checks on Linearity Assumption in the JHPS. Panel A plots the values of age dummies in the fixed effects estimation with discount rates as the dependent variable controlling for risk attitudes and the interest rate. In Panel B, the dependent variable is the discount rate adjusted for background consumption. We run a fixed effects regression controlling for interest rate. The bars indicate 95% confidence intervals.

background consumption generally makes the estimated discount rates smaller and due to measurement error in consumption standard errors become large. Still, we observe the negative relationship between age and discount rates.

B.2 Alternative Ways of Capturing Year and Cohort Effects

In the main text, we approach the issue of perfect collinearity between age, birth year and survey year by using macro variables as substitutes for calendar year effects. In addition in Section 5.1, we provide evidence that our results are not sensitive to the specific choice of the proxy variable.

In this section, we present two alternative ways of approaching the identification issue. First, we use proxies to substitute cohort effects instead of proxies for survey year effects. Motivated by Robson and Samuelson (2011) and Falk et al. (2019), we use life expectancy and population growth as proxies for cohort effects. We measure both variables at age 20 in line with the literature on personal experiences, which points to the importance of the so-called formative years (see e.g. Giuliano and Spilimbergo, 2014).



(A) Proxy Cohort Effects

(B) Group Year Dummies

Figure B.2: Robustness Check: Capture Cohort and Year Effects. In Panel A we run an OLS regression of discount rates on age, controlling for year dummies as well as population growth and life expectancy to capture cohort effects. Panel B plots the values of age dummies in the individual fixed effects estimation with discount rates as the dependent variable controlling for 3-calendar year group dummies.

We regress the discount rate on these cohort proxies as well as on age dummies and include dummies for each survey year. The survey year dummies capture all kinds of year specific events and developments that affect measured time preferences. The results are depicted in Figure B.2A. In line with the main results, the discount rate decreases with age.

As a second alternative to our main approach, we include group year dummies for periods of three consecutive survey years to capture calendar year effects (i.e. we include separate dummy variables for the periods 2010–2012, 2013–2015 and 2016–2018) and allow for individual fixed effects to capture cohort effects. The approach has the advantage that we do not have to choose proxy variables for either birth years or survey years and we still resolve the issue of perfect collinearity of age, cohort and survey years. The underlying assumption is that macro events and developments affect measured discount rates for a longer period than just one year. Figure B.2B shows that this alternative approach confirms our finding of a roughly linearly downward sloping age effect.

Table B.2: Controlling for Pre-Determined Socioeconomic and Subjective Health Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	-0.205***	-0.158***	-0.172***	-0.177***	-0.177***	-0.177***	-0.172***
	(0.052)	(0.053)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Interest Rate	0.072	0.346***	0.212***	0.213***	0.213***	0.213***	0.213***
	(0.096)	(0.102)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Cohort FE	YES	YES	YES	YES	YES	YES	YES
Log Income	NO	NO	YES	NO	NO	NO	YES
Financial Wealth	NO	NO	NO	YES	NO	NO	YES
Health Status	NO	NO	NO	NO	YES	NO	YES
Wealth to Income	NO	NO	NO	NO	NO	YES	YES
Education Sample	LOW	HIGH	ALL	ALL	ALL	ALL	ALL
Observations	11078	8387	20906	20906	20906	20906	20906
R^2	0.022	0.038	0.019	0.017	0.016	0.016	0.020

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. We estimate ordinary least square models with discount rates as the dependent variable. Clustered standard errors at the individual level are reported in parentheses. All the control variables and education are measured in 2010. The low education sample consists of individuals with less than a college degree, whereas the high education sample has a college degree or more. Log income is defined as the log of the total household after-tax income. Financial wealth is defined as the sum of "saving and deposit" and "securities". The Wealth to Income ratio is computed as financial wealth divided by the total household after-tax income. The health status is based on a subjective assessment of the own health status.

B.3 Controlling for Socioeconomic Characteristics

In Table 5, we present results for our main individual fixed effects regressions controlling for several socioeconomic and health variables. These controls are measured contemporaneously. In Table B.2, we run pooled OLS regressions including cohort fixed effects for every birth year and controlling for the socioeconomic characteristics and the health status as measured in 2010 (the first year of our sample). By construction, these pre-determined variables do not vary over time and, thus, cannot be included in an individual fixed regressions. Reassuringly, the result are very much in line with those reported in Table 5.

C Derivations and Robustness for Section 3.2

Derivation of equation (5) Applying the second-order Taylor expansion on the right-hand side of equation (3), we obtain

$$u(c) = (1-\pi)\left[u(c) + (-z)\,u'(c) + \frac{(-z)^2}{2}u''(c)\right] + \pi\left[u(c) + (-z+x)\,u'(c) + \frac{(-z+x)^2}{2}u''(c)\right].$$

Using the expression (4), it follows that

$$\begin{aligned} 0 &= (1-\pi)\,(-z)\,c + (1-\pi)\frac{z^2}{2}\frac{u''(c)}{u'(c)}c + \pi\,(-z+x)\,c + \pi\frac{(-z+x)^2}{2}\frac{u''(c)}{u'(c)}c \\ &= (1-\pi)\,(-z)\,c - (1-\pi)\frac{z^2}{2}\gamma + \pi\,(-z+x)\,c - \pi\frac{(-z+x)^2}{2}\gamma. \end{aligned}$$

Rearranging terms yields equation (5).

Derivation of equation (6) Assuming a time-invariant utility function, we first consider an indifference relationship for intertemporal choices:

$$u\,(c_t + P) + e^{-\rho}u(c_{t+1}) = u\,(c_t) + e^{-\rho}u(c_{t+1} + F),$$

where (P,F) are hypothetical payments in the monetary discounting question.[6] We can then write

$$e^{-\rho} = \frac{c_t^{1-\gamma} - (c_t + P)^{1-\gamma}}{c_{t+1}^{1-\gamma} - (c_{t+1} + F)^{1-\gamma}}. \tag{C.1}$$

Consumption data might contain measurement error, which potentially biases the estimation of time preferences. For example, Heathcote et al. (2014) find that 29.6% of the variance of log consumption in cross section in the U.S. is due to measurement error. This issue is even more problematic when one uses the panel dimension of consumption because c_t and c_{t+1} are each powered by $1-\gamma$, which would exacerbate the issue of measurement error. Thus, similar to Andersen et al. (2008), we use contemporaneous

[6] We abstract from expectation. To estimate the expectation, one needs to know underlying income processes as well as individual access to credit markets, which is quite challenging and thus often disregarded in the literature.

consumption in the main analysis and obtain

$$e^{-\rho} = \frac{c^{1-\gamma} - (c+P)^{1-\gamma}}{c^{1-\gamma} - (c+F)^{1-\gamma}},$$

which yields equation (6).

Discount Rates with Time-Varying Relative Risk Aversion Equation (C.1) assumes a time-invariant utility function. In Section 3.2, we compute γ by the average of all available years in the data (2005-2008). The assumption of a constant γ allows us to extend the panel analysis to the year 2009 when the question about risk preferences is no longer available, but that about time preferences still is.

Now we relax this assumption and allow for time-varying relative risk aversion. Specifically, we restrict the sample to the years where we have information on risk preferences (i.e. from 2005 to 2008) and use γ from the same period. Figure C.1A shows a downward sloping age pattern, so the results are robust to this specification. Given the smaller sample size and the shorter panel dimension, standard errors become larger as compared to the main results presented in Section 3.2.

Discount Rates with Lead Consumption In Section 3.2, we only use contemporaneous consumption. We now relax this assumption and instead estimate equation (C.1).

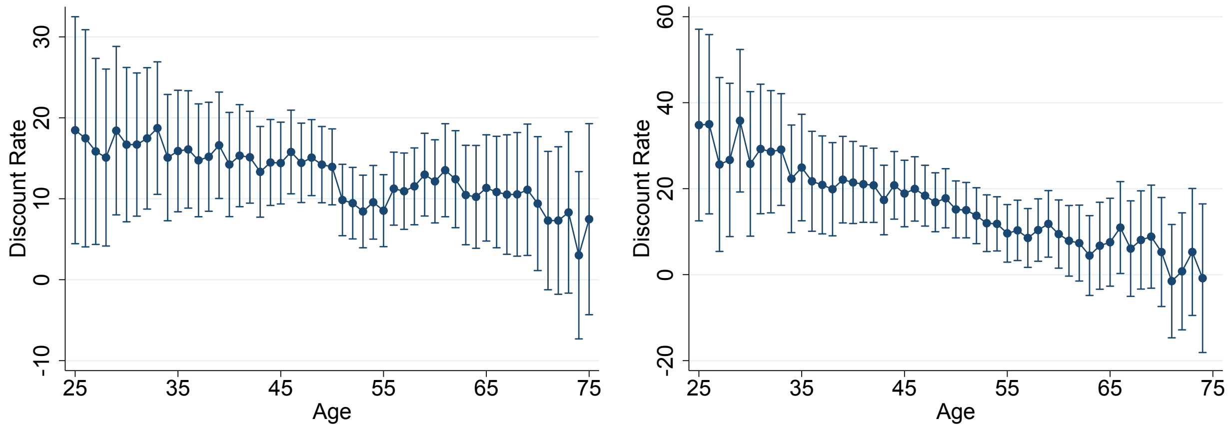
Estimating this equation is challenging due to possible measurement error in consumption. To see this, we rewrite the equation as

$$e^{-\rho} = \frac{\left(\frac{c_t}{c_{t+1}}\right)^{1-\gamma} - \left(\frac{c_t+P}{c_{t+1}}\right)^{1-\gamma}}{1 - \left(\frac{c_{t+1}+F}{c_{t+1}}\right)^{1-\gamma}}.$$

It makes clear that a change in consumption over time, which is possibly due to measurement error, is amplified by the power $1-\gamma$, and thus estimated ρ could become an extremely large value in an absolute term.

To mitigate the issue of measurement error, we take five-year moving averages of consumption and drop the outliers with the top or the bottom 5% of discount rates.

Figure C.1B plots the age effects estimated in the fixed effects model (2). We find a negative relationship between age and discount rates in this case too. The downward



(A) With Time-Varying Risk Aversion

(B) With Lead Consumption

Figure C.1: Robustness for Age Patterns and Curvature of Utility Function. The figure plots the values of age dummies in the individual fixed effects estimation. The dependent variable is discount rates with adjusting for curvature of utility function. Panel A uses time-varying relative risk aversion. Panel B uses lead consumption. The bars indicate 95% confidence intervals.

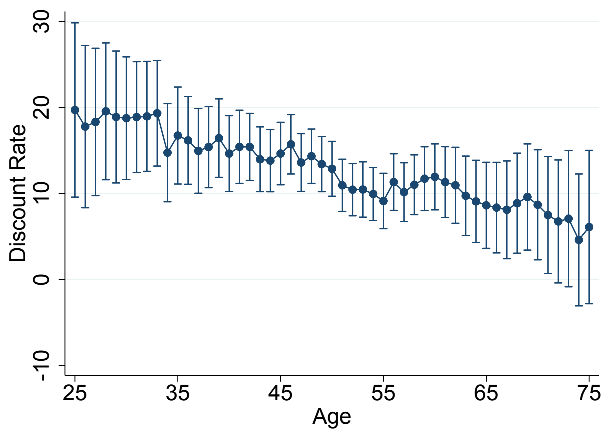
slope is steeper than that in Figure 4B.

Using the Full Sample In Section 3.2, we exclude outliers from the sample by dropping the top and the bottom 1% based on the curvature-adjusted discount rates. In Figure C.2, we repeat the same analysis using the full sample instead. Figure C.2A shows that, without adjustment for curvature, including the outliers hardly affects the results. The age patterns in Figure C.2B are also similar to those in Figure 4B, while the standard errors become larger.

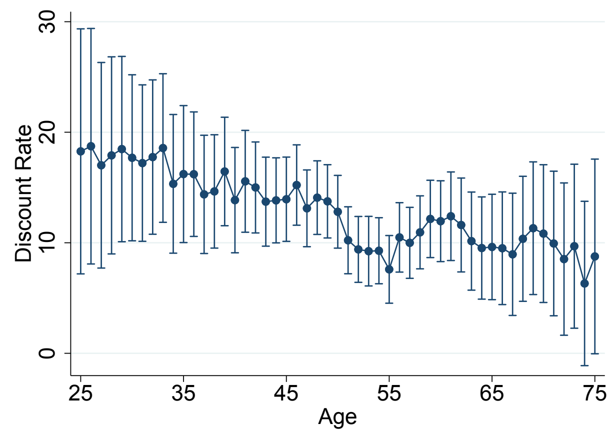
D Quantitative Analysis

D.1 Estimating the Income Process

The estimation of the income process (8) follows Arellano et al. (2017) and De Nardi et al. (2020).



(A) Without Adjustment for Curvature



(B) With Adjustment for Curvature

Figure C.2: Robustness for Age Patterns and Curvature of Utility Function in the Full Sample. The figure plots the values of age dummies in the individual fixed effects estimation. The dependent variable is discount rates with/without adjusting for curvature of utility function. The bars indicate 95% confidence intervals.

Panel Data For the income process estimation, we use data from the JHPS from 2010 to 2018 and focus on married couples, where the husband is aged between 25 and 64. To measure earnings we use total after-tax household labor earnings deflated to the year 2015. We use disposable household earnings, rather than pre-tax individual earnings, because we want to capture underlying earnings risk for consumption insurance, which requires taking into account that households and taxes provide insurance against earnings shocks. We compute total after-tax household earnings as follows: The JHPS includes information on the total household after-tax income. We thus have to subtract income from other sources than labor. We do so by adding up income from rent and land rent as well as from interest and dividends of all household members. As the financial income is given as pre-tax income, we compute the amount of taxes payed on this income source by applying a tax rate of 20.315%—the prevailing tax rate on interest and dividends in Japan since 2013. Finally, we subtract after-tax financial income from total household after-tax income to get a measure of household after-tax labor earnings. We include observations with non-missing information on labor earnings, on the key demographic variables used to construct the earnings residuals (described below), and on time preferences. To create a balanced panel, we consider all sets of consecutive four-year observations. We construct residual labor earnings by regressing log total after-tax household labor earnings on education categories for both spouses, household size, the number of kids living in the household and a dummy for kids out of the household, a dummy for income recipients other than husband and wife, metropolitan areas, geographic area dummies, and survey year dummies.

Deterministic Age Profile The deterministic age component κ is estimated by regressing residual earnings on a fourth-order Hermite polynomial in age.

Quantile-Based Framework We consider the quantile-based framework for the estimation of the persistent component η and transitory component ε.

Let $Q_x(p|\cdot)$ be p-th conditional quantile of the variable x, i.e., the conditional mapping such that $\Pr\{x \leq Q_x(p|\cdot)\} = p$. We assume that the persistent component η follows a first-order Markov process. For each age $t > 1$ and any random draw $p \sim U(0,1)$, we can write

$$\eta_t = Q_\eta(p|\eta_{t-1}, t).$$

The advantages of this general structure are threefold. First, it does not impose age-independence of the autocorrelation of the shocks.[7] Second, it allows the shock distribution to be different from being normal. Third, the process can be nonlinear.

Likewise, we consider similar unrestricted (but not persistent) representations for the transitory component $\varepsilon_t = Q_\varepsilon(p|t)$ and the initial condition $\eta_1 = Q_{\eta_1}(p|1)$.

Empirical Implementation We empirically specify the quantile functions above by

$$\begin{aligned}
Q_\eta(p|\eta_{i,t-1}, age_t) &= \sum_{k=0}^{K} a_k^{\eta}(p)\,\varphi_k(\eta_{i,t-1}, age_{i,t}), \\
Q_\varepsilon(p|age_{i,t}) &= \sum_{k=0}^{K} a_k^{\varepsilon}(p)\,\varphi_k(age_{i,t}), \\
Q_{\eta_1}(p|age_{i,1}) &= \sum_{k=0}^{K} a_k^{\eta_1}(p)\,\varphi_k(age_{i,1}),
\end{aligned}$$

[7] The persistence of the shocks is given by $\partial Q_\eta(v|\eta_{t-1}, t)/\partial \eta_{t-1}$ that is in general dependent on age.

for a draw $p \sim U(0,1)$, where $age_{i,t}$ is age of the male spouse i in period t, the coefficients a are modelled as piecewise-linear splines in p, and φ are bivariate functions. Following Arellano et al. (2017), for φ we use tensor products of Hermite polynomials of degrees $(3,2)$ for η and second-order Hermite polynomials for ε and η_1.

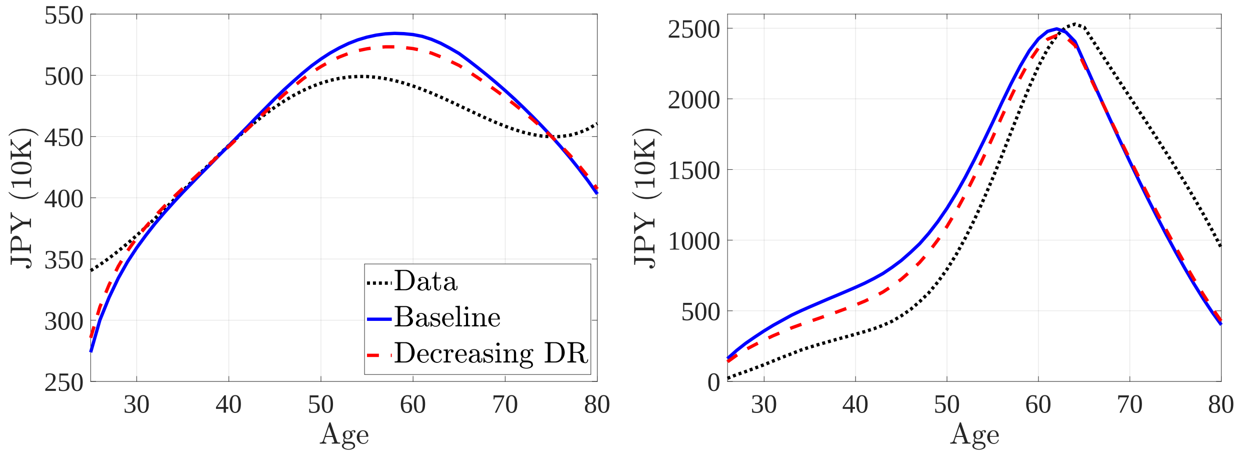
Estimating Markov Chains To expand the sample, we simulate the estimated model specified above for a large set of histories for the persistent and transitory component of earnings. We then estimate first-order Markov chains in the simulated sample with N-dimensional age-dependent state spaces and transition matrices. While the set of states and the transition matrices are age-dependent, their dimension N is assumed to be constant across ages.

For this estimation, we follow De Nardi et al. (2020). First, at each age, the realizations of each component are ordered by the size and grouped into N bins. For η, we use 10 bins with bins 1–2 and 9–10 including 2.5% of agents, 3 and 8 including 5% and 4-7 each having 20% of agents. For ε, we use 8 bins with bins 1–2 and 7–8 including 2.5% of agents, 3 and 6 including 5% and 2 and 3 each having 40% of agents. Next, we use the median of each bin at age t to determine the state spaces. Finally, the transition matrices are given by estimating the fraction of agents transiting from one bin at age t to another bin at age $t+1$.

D.2 Life-cycle Profile of Consumption and Asset Holdings

Figure D.1 plots consumption and asset holdings profiles over the life cycle for the baseline canonical life-cycle model, the model with decreasing discount rates and the data.

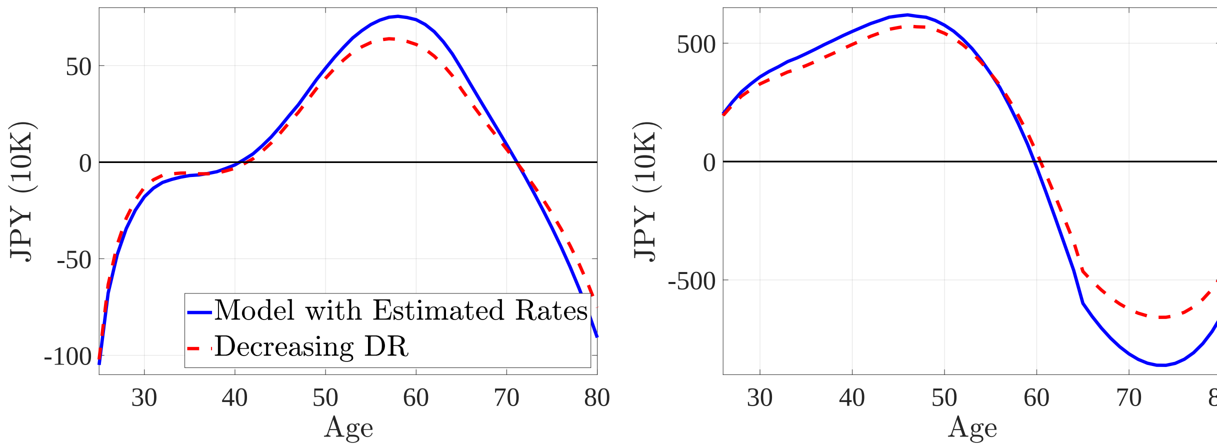
Comparing the data profile (black dotted line) with the prediction of the baseline model with constant discount rates (blue solid line), Figure D.1A shows that even the very simple canonical model considered in Section 4 does a good job in replicating the overall hump-shaped consumption and asset profiles. The figure also shows that considering decreasing discount rates in this simple model leads the prediction in the right direction.



(A) Consumption

(B) Asset Holdings

Figure D.1: Predictions of the Canonical Life-Cycle Model in Level. The figure plots the consumption (panel A) and asset holdings (panel B) profile over the life cycle for the baseline model with constant discount rates (blue solid), the model with decreasing discount rates (red dashed) and the data (black dotted). The data profiles are smoothed by regressing on a fourth-order Hermite polynomial in age. The asset profiles are constructed using income and consumption profiles together with the budget constraint.



(A) Consumption

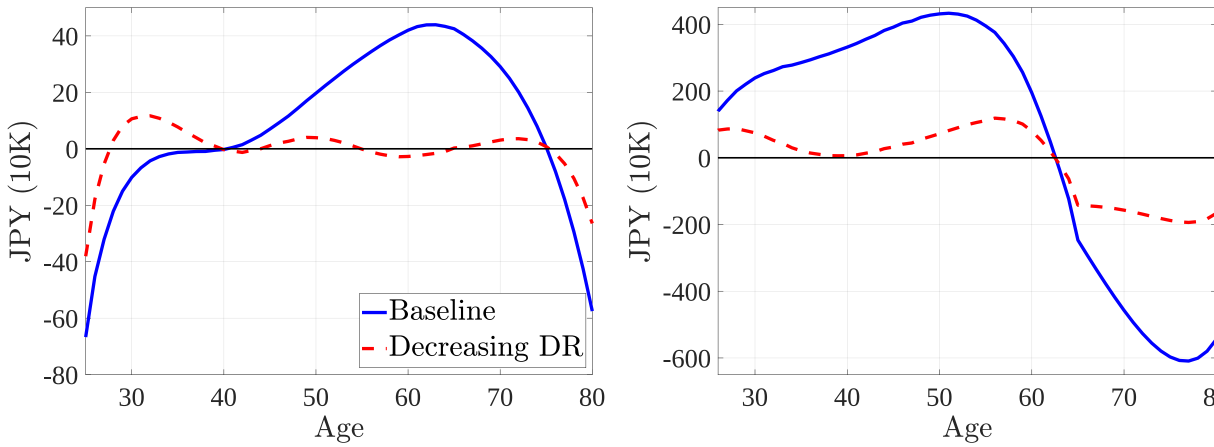
(B) Asset Holdings

Figure D.2: Predictions of the Canonical Life-Cycle Model with Estimated Discount Rates. The figure plots the consumption (panel A) and asset holdings (panel B) profile over the life cycle for the baseline model with constant discount rates (blue solid), and the model with decreasing discount rates (red dashed), relative to the data.

D.3 Alternative Calibrations

In the main quantitative analysis, we calibrated the average discount factor, rather than using the direct estimate of discount rates. Also, for the experiment of decreasing discount rates, we impose a 1.3% decrease rather than a level decrease of 0.19 percentage points. This is because the level of discount rates depends on the empirical model and thus might be more sensitive to the model specification than the estimated slope. In this section, we consider alternative calibrations.

Model with Direct Estimate of Discount Rates. First, we calibrate only γ and use the direct estimate of discount rates we found in Section 3.1. Namely, we consider $\beta = e^{-\rho}$ where $\rho = 0.1414$ for the baseline model with constant discounting. The calibrated γ is given by 5.467, which is considerably higher than the one we found in the main analysis but still remains in the reasonable range. For the experiment of decreasing discount rates, we consider an annual decrease of 0.19 percentage points, which we also found in Section 3.1. Evaluated at the average discount rates, this amounts to a 1.3% decrease as in the main analysis. The recalibrated γ is given by 5.601.



(A) Consumption (B) Asset Holdings

Figure D.3: Predictions of the Canonical Life-Cycle Model with Estimated Level Decrease in Discount Rates. The figure plots the consumption (panel A) and asset holdings (panel B) profile over the life cycle for the baseline model with constant discount rates (blue solid), and the model with decreasing discount rates (red dashed), relative to the data.

Figure D.2 is the analogous figure to Figure 5. It shows that using the direct estimate of the discount rate, the model fit becomes generally worse, because we are now calibrating only one parameter. However, the qualitative pattern stays the same; with decreasing discount rates, agents accumulate less assets when young and more when old, making the asset profile flatter and closer to the data. The model's prediction about consumption and savings behaviors is again significantly improved; measured by the sum of squared errors, the model's fit to the consumption and asset profiles increases by 27.1% and 30.1%, respectively.

Model with Estimated Level Decrease in Discount Rates. Next, we use the same baseline model as in Section 4, but for the experiment of decreasing discount rates, we consider an annual decrease of 0.19 percentage points, which we found in Section 3.1. The recalibrated parameter values are given by $\gamma = 1.566$ and $\beta = 1.043$, where the latter is the average over the life.

Figure D.3 is the analogous figure to Figure 5. It shows that using the estimate level decrease in the discount rates, the model's prediction about consumption and savings behaviors is substantially improved; measured by the sum of squared errors, the model's fit to the consumption and asset profiles increases by 91.2% and 92.1%, respectively. This large improvement stems from the fact that the estimated level decrease is much larger than the change considered in the baseline model. However, the qualitative pattern stays the same.

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