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Time Preferences over the Life Cycle*

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Abstract

We study whether and how time preferences change over the life cycle, exploiting representative long-term panel data. We estimate the age patterns of discount rates from age 25 to 80. In order to identify age effects, we have to disentangle them from cohort and period factors. We address this identification problem by estimating individual fixed effects models, where we substitute period effects with determinants of time preferences that depend on calendar years. We find that discount rates decrease with age and the decline is remarkably linear over the life cycle.

Keywords: Time Preferences; Preference Stability; Age; Discount Rates

JEL classification: D01, D12, D91, J10

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1 Introduction

A key assumption of the discounted-utility model (Samuelson, 1937) and its variants including the life-cycle model is that time preferences 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 much of welfare analyses and policy evaluations. 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 in empirical studies that disentangling age effects from influences of period-specific and cohort-specific factors is difficult. This identification problem might explain why previous studies find mixed results about the age effects on 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 in Japan surveyed since 2009. The JHPS provides key information about time preferences based on a hypothetical question that is experimentally validated. One advantage of using this information is that answers to the question are convertible to standard 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.[3]

The identification problem arises 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

[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).

[3]The lack of longitudinal studies on time preferences has been long 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 in two-year panel data from experiments in Seattle/Denver (Krupka and Stephens Jr, 2013), in Boston (Meier and Sprenger, 2015), and in rural Paraguay (Chuang and Schechter, 2015).

measured time preferences. Age could affect time preferences for biological reasons, e.g., through the conditional life expectancy at a given age. Rogers (1994) argues that time preferences are associated with reproductive potential, which varies with age. 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 time preferences through experiences. 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).[4] 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 Consumer Price Index (CPI) and real interest rates 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 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. It is crucial to account for cohort effects; the negative and roughly linear relationship 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 0.48 percentage points decrease in the measured discount rates.

Our findings are robust to various other specifications. First, we find a similar linear negative relationship between age and discount rates for both genders. Second, our results are not sensitive to the specific choices of proxy for the calendar year such as GDP growth (Hardardottir, 2017) and/or stock market returns (i.e., Nikkei 225 return). Third, our findings are robust to controlling for socioeconomic characteristics such as educa-

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

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%

tion, income or wealth (Fisher, 1930; Becker and Mulligan, 1997), or the extent to which a household is liquidity constrained. Finally, we show that our results are virtually identical even when we control for individual risk attitudes, addressing the concern that measured time preferences could be potentially biased if the underlying utility function is strictly concave (Andersen et al., 2008).

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.[5] We select individuals aged 25 to 80 and drop observations with missing answers to the question on time preferences.[6] 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.

[5]See Appendix A for details of the data set. The JHPS starts in 2009, but we use the data from 2010 because after that the question regarding time preferences is identical.

[6]We restrict our attention to the age range for which there is a sufficient number of individuals. The mean and the standard deviation of age are given by 53.9 and 14.7, respectively.

Our measure of time preferences is elicited directly from a hypothetical question in the JHPS. Elicitation is done by a version of matching tasks; respondents are asked about, instead of receiving 10 thousand Japanese yen (JPY) one month later, at least how much they would like to receive 13 months later.[7] 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, we then convert it to discount rate ρ as follows:[8]

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

This type of hypothetical questions are experimentally validated and still a major tool to elicit time preferences (e.g., Dohmen et al., 2010; Ifcher and Zarghamee, 2011; Meier and Sprenger, 2015).[9] Note that the hypothetical question we rely on 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 (Johnson and Bickel, 2002; Madden et al., 2003; Vischer et al., 2013; Falk et al., 2016). Moreover, a number of studies document that time preferences elicited by hypothetical questions 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).[10] Golsteyn et al. (2014) also find that adolescent measured time preferences predict school performance, health, labor supply, and lifetime income.

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

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

[8] 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).

[9] Frederick et al. (2002) provide an extensive survey of early studies for eliciting time preferences. They also discuss important assumptions for measuring discount rates in this way. We address a potential concern about the concavity of the utility function in Section 4 (see Andersen et al., 2008).

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

data set that allows measuring discount rates annually for such a long time.[11] 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, possibly because of the low complexity of processing the hypothetical question, the nonresponse rate to this question is quite low (1.9% of all observations). Fourth, unlike hypothetical questions using Likert scales, 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.

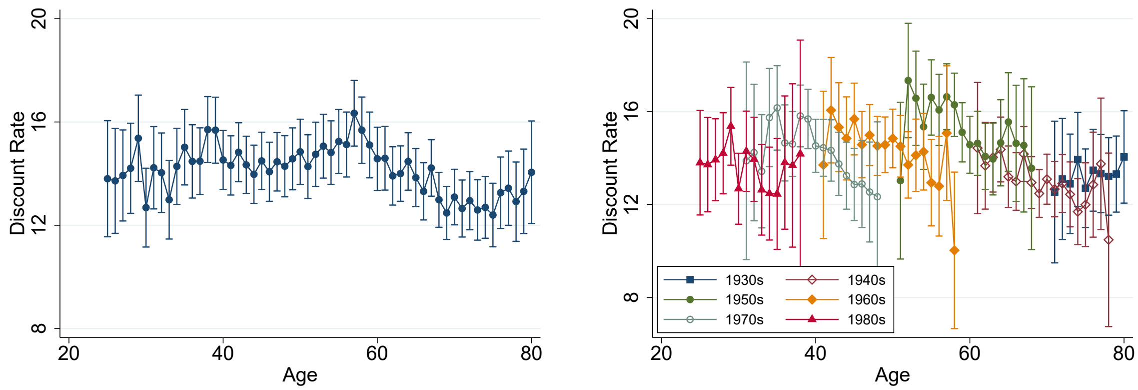
2.2 Empirical Strategy

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 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 macroeconomic factors measured in a particular survey year as substitutes for calendar time.

The macroeconomic proxy variables help resolve the identification problem if they meet the following conditions. First, they have to be related to measured time preferences. Second, they have to vary with calendar time but not in a linear fashion. As for

[11] Kuralbayeva et al. (2019) use a representative panel data set in Italy that asks a hypothetical question on time preferences four times between 2004 and 2014 and study how the earthquake in 2009 affected individual time preferences.



(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.

the first condition, given the theoretical considerations in Frederick et al. (2002), in our main specification, we choose CPI and real interest rates in particular years as proxies for period effects.[12] Figure 2 depicts the evolution of measured discount rates as well as CPI (Panel A) and real interest rates (Panel B) between 2010 and 2018, the time period under consideration. It shows that the two macro variables vary with calendar time, but not in a linear way, satisfying the second condition.

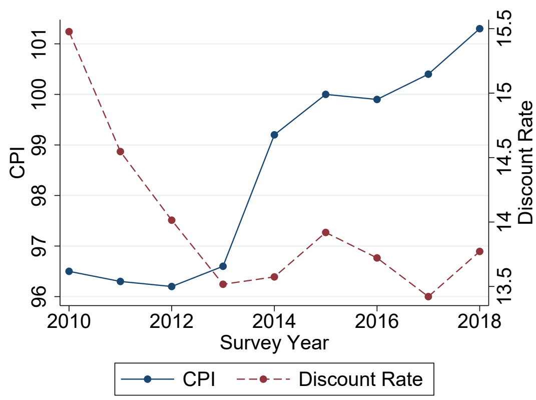
We estimate the following fixed effects model:

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

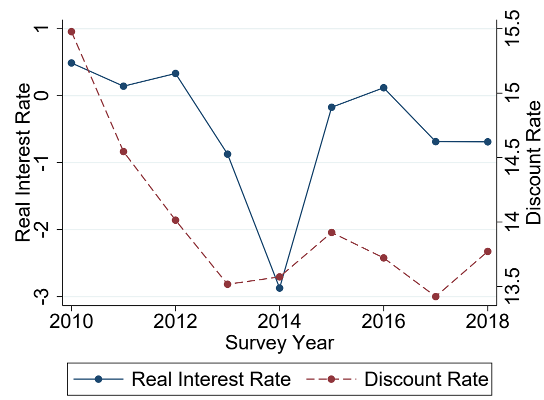
The dependent variable ρ_{it} is the measured discount rate of individual i in period t calculated in equation (1). We control for individual fixed effects α_i, which capture, among others, cohort effects. In the baseline specification, we consider a full set of age dummies *age*. The vector $macro_t$ consists of the CPI and real interest rates 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.[13]

[12] Krupka and Stephens Jr (2013) provide empirical evidence that inflation and real interest rates are related to measured discount rates.

[13] 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



(A) CPI



(B) Real Interest Rate

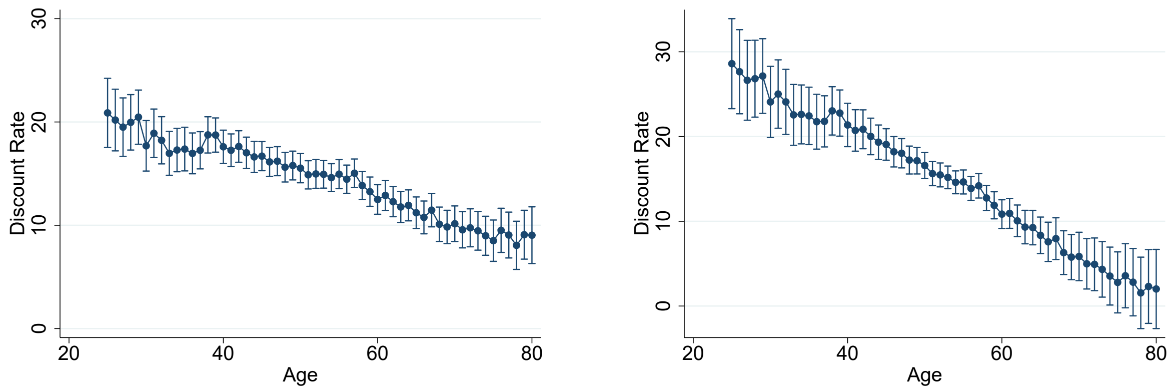
Figure 2: Macro Variables and Discount Rates. The figure plots measured discount rates (right y-axis) along with two macro variables (left y-axis), namely CPI (Panel A) and real interest rates (Panel B). The data for CPI are obtained from the Ministry of Internal Affairs and Communications in Japan and the base year is 2015. Real interest rates are constructed using the Fisher equation with the data for nominal interest rates, which are the average interest rates posted on time deposits obtained from the Bank of Japan.

3 Results

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 variables in Panel B makes the estimated age effects steeper.

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 2 presents the results. We include individual fixed effects in all specifications and introduce the independent variables successively: column (1) only includes age, columns (2) and (3) separately add the two macro variables (i.e., CPI and real interest rates), and column (4) includes both macro variables, which is our main specification. Throughout, the coefficient of age is negative and statistically significantly different from zero. The estimate in column (4) suggests that a one-year increase in age is associated with a decrease in the measured

would result in a spurious negative relationship between age and discount rates. In Appendix B, we provide supportive evidence that selective non-response is generally not a concern in the JHPS irrespective of model specifications.



(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.

discount rate by 0.48 percentage points. Evaluated at the average discount rate in the sample of 14.14, this amounts to a 3.4% decrease in the discount rate. Both the CPI and real interest rates are positively related to the measured discount rates.

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). 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. Using an evolutionary biology approach, Rogers (1994) shows that age-dependent reproductive potential generates a decreasing age profile for subjective discount rates among sexually matured adults. Halevy (2005) also shows that diminishing impatience would emerge for a decision maker with time-consistent preferences when lifetime is uncertain.[14]

4 Robustness

In this section, we show that our results are robust to various alternative specifications. The details and more robustness checks are presented in Appendix C.

[14]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 2: Age Effects on Discount Rates

	(1)	(2)	(3)	(4)
Age	-0.219	-0.478	-0.187	-0.478
	(0.037)	(0.082)	(0.037)	(0.082)
CPI		0.371		0.426
		(0.108)		(0.110)
Real Interest Rate			0.235	0.284
			(0.072)	(0.073)
Individual FE	YES	YES	YES	YES
Observations	21000	21000	21000	21000
R^2	0.533	0.533	0.533	0.534

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.

Gender Our results are robust to both genders. To see this, we estimate the fixed effects model (2) separately for males and females. The estimated discount rates are roughly linearly decreasing with age, as in the baseline model (Figure C.1). 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).

Alternative Controls for Period Effects In our baseline specification, we use CPI and real interest rates as substitutes for period effects. We still find negative and significant, although somewhat smaller, age effects, when we instead use GDP growth (Hardardottir, 2017) and/or stock market returns (i.e., Nikkei 225 return), see Table C.1. The results are thus not very sensitive to the specific choices of proxy for the calendar year.

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 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. Our results are also robust to controlling for these variables, see Table C.2.

We also consider the extent to which a household is liquidity constrained. Since young households are more likely to be liquidity constrained and tighter constraints would make agents more impatient, our result of age effects might be driven by liquidity needs. To address this concern, we construct a variable for the degree of household liquidity as financial wealth divided by disposable income. We then calculate an indicator variable for hand-to-mouth, assigning 1, instead of 0, to households whose degree of liquidity is below one-sixth, following Zeldes (1989). Reassuringly, the estimates of age effects are unchanged when we control for liquidity needs by the hand-to-mouth indicators (Table C.2).

Concavity of Utility Function A key assumption to elicit time preferences using the hypothetical question is that the utility function is linear for small stakes outcomes. Rabin (2000) shows that this 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).[15] Andersen et al. (2008) argue that with a concave utility function, estimated discount rates would be upward-biased. To correct for this bias, a joint elicitation of time and risk preferences has been proposed in several studies (Andersen et al., 2008; Andreoni and Sprenger, 2012). However, since the true utility function is never observed, one still has to make assumptions about the form of the utility function.

We address this issue by adding a control to our main specification for directly observed risk attitudes measured by a survey question, similar to Dohmen et al. (2007) and Meier and Sprenger (2015). 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. We show that this risk measure is positively and statistically significantly related to the share of risky assets in total financial assets and risky behaviors such as smoking and alcohol consumption (Table C.3), controlling for age and education. We also estimate an individual fixed effects model with our risk attitude measure as the dependent variable and find a downward sloping pattern of age effects over the life course (Figure C.2A), similar to Dohmen et al. (2017) who use a survey measure of risk attitudes that is validated as being predictive of risky choice. 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 additional control to the fixed effects estimation (equation 2). Figure C.2B shows that the age effects are virtually identical to our main result in Figure 3B.

[15] 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.

5 Conclusions

In this paper, we exploit representative long-term panel data in Japan and estimate age patterns of discount rates. We conclude that time preferences do change over the life course. We find that discount rates decrease with age and the decline is remarkably linear over the life cycle.

Our finding has important implications for research in economics and policymakers. For example, it is important to consider age-dependent discount rates in life-cycle models for studying consumption dynamics or savings behavior. For the estimation of life-cycle models, it would be appropriate to allow for discount rates that can change over the life course.

For policymakers, many countries nowadays introduce private pension plans as supplements of public systems to encourage individual retirement savings through tax advantages or benefits from government subsidies (e.g., 401k for the U.S.). Our result suggests that these programs would affect young and old adults differently, and thus age-dependent incentive programs would work more effectively. Moreover, our results may be of interest for monetary policymakers. If a lower discount rate is associated with a higher saving rate, population aging may entail an increase in aggregate household savings, which is likely to put downward pressure on the natural rate of interest.

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Time Preferences over the Life Cycle

Online Appendix

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Hitoshi Tsujiyama Midori Wakabayashi

A Japan Household Panel Survey

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.

We use the data from 2010 because after that 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.

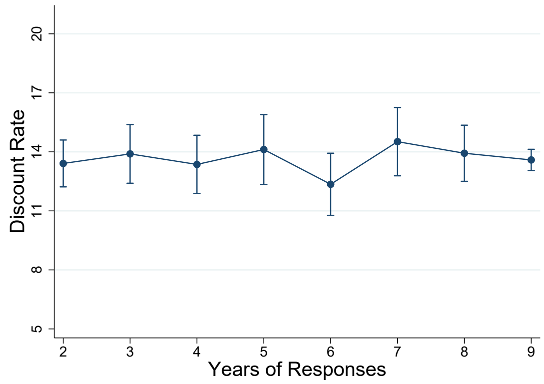
Our measure of time preferences is elicited from a hypothetical question in the JHPS. Since 2010, participants of the survey were asked the same question annually to elicit their discount rates: "Instead of receiving 10 thousand yen one month later, at least how much would you like to receive 13 months later? Please choose one option from the following options 1–8":[2]

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%

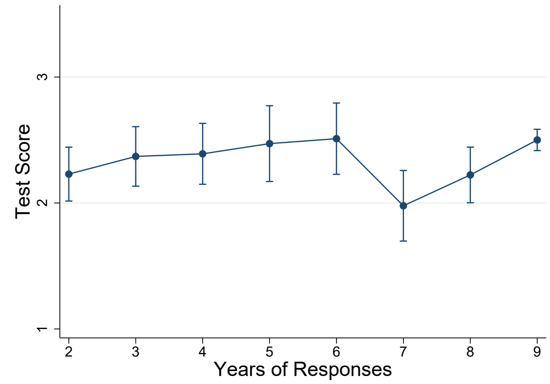
From the answers to this question, we calculate an internal rate of return r that is used in equation (1).

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

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



(A) Years of Responses and Discount Rates



(B) Years of Responses and Test Scores

Figure B.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.

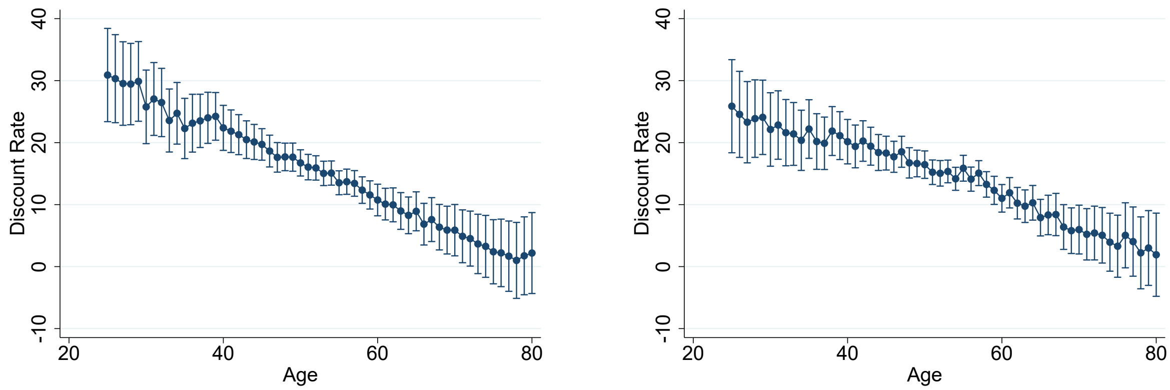
There are few observations who choose the first option (0.003%), which cannot be rationalized by any utility-maximization theory. We did not exclude these samples; excluding them does not change our results.

B 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 B.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 samples 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



(A) Males

(B) Females

Figure C.1: 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 macro variables separately for males and females. The bars indicate 95% confidence intervals.

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.[3] 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 B.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.

C Robustness

This section provides details of the robustness checks discussed in Section 4.

Gender Our results are robust to both genders. Figure C.1 plots the age dummies from the fixed effects model (2) separately for males and females. The estimated discount rates are linearly decreasing with age, as in the baseline model. The slope of age effects is

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

Table C.1: Alternative Controls for Period Effects

	(1)	(2)	(3)
Age	-0.182***	-0.215***	-0.174***
	(0.038)	(0.037)	(0.038)
GDP Growth	-0.097***		-0.105***
	(0.030)		(0.031)
Stock Market Returns		-1.298***	-1.390***
		(0.334)	(0.337)
Individual FE	YES	YES	YES
Observations	21000	21000	21000
R^2	0.533	0.534	0.534

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.

slightly steeper for males than for females, and females have somewhat lower discount rates (except for the very old).

Alternative Controls for Period Effects In Table C.1, we use GDP growth and/or stock market returns (i.e., Nikkei 225 return) as substitutes for period effects. Our findings do not change and thus are not very sensitive to the specific choices of proxy for the calendar year.

Socioeconomic Status We account for the socioeconomic status variables such as education, income, and/or financial wealth. As the education level does not vary 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. Column (1) of Table C.2 refers to the low education group, and column (2) refers to the high education sample. To control for income (columns (3) and (6) of Table C.2), we take the log of the total household after-tax income. Financial wealth is defined as the sum of "saving and deposit" and "securities" minus non-mortgage loan (e.g., credit card loan). The latter is imputed by subtracting outstanding mortgage loan from total debt. We control for it in columns (4) and (6) of Table C.2. Table C.2 shows that including socioeconomic status variables does not change the results.

Table C.2: Controlling for Socioeconomic Status

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.547***	-0.318***	-0.461***	-0.494***	-0.493***	-0.495***
	(0.117)	(0.118)	(0.089)	(0.087)	(0.092)	(0.092)
CPI	0.497***	0.191	0.386***	0.450***	0.426***	0.419***
	(0.157)	(0.162)	(0.120)	(0.117)	(0.124)	(0.123)
Real Interest Rate	0.199*	0.334***	0.254***	0.265***	0.261***	0.268***
	(0.103)	(0.112)	(0.078)	(0.077)	(0.081)	(0.081)
Individual FE	YES	YES	YES	YES	YES	YES
Log Income	NO	NO	YES	NO	NO	YES
Net Financial Wealth	NO	NO	NO	YES	NO	YES
Hand to Mouth	NO	NO	NO	NO	YES	YES
Education Sample	LOW	HIGH	ALL	ALL	ALL	ALL
Observations	11087	8400	18364	18867	17267	17330
R^2	0.517	0.555	0.548	0.540	0.553	0.553

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.

We also construct a variable for the degree of household liquidity as financial wealth divided by disposable income. We then calculate an indicator variable for hand-to-mouth, assigning 1, instead of 0, to households whose degree of liquidity is below one-sixth, following Zeldes (1989). Columns (5) and (6) of Table C.2 show that the results are robust when we control for this variable.

Concavity of Utility Function 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?". Answers 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 (i.e., willingness to take risks).

Is this measure a valid measure for risk attitudes? In Table C.3, we show that our risk attitude measure is positively and statistically significantly related to the share of risky assets in total financial assets and risky behaviors such as smoking and alcohol consumption, controlling for age and education. The share of risky assets is defined by securities divided by total financial assets. 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

Table C.3: Risk Preference Correlates

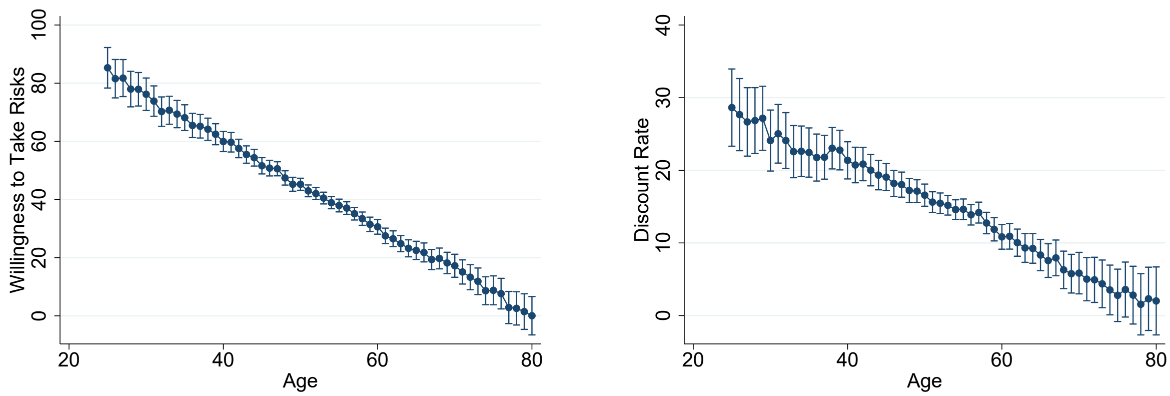
Dependent Variable	(1) Share of Risky Assets	(2) Share of Risky Assets	(3) Smoking Frequency	(4) Alcohol Consumption
Risk Attitudes	0.014**	0.016**	0.004***	0.003***
	(0.007)	(0.007)	(0.000)	(0.000)
Education	YES	YES	YES	YES
Age	YES	YES	YES	YES
Total Financial Assets	NO	YES	NO	NO
Observations	15992	15992	22159	22035
R^2	0.053	0.102	0.039	0.029

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.

alcohol consumption variable is defined by the drinking frequency (i.e., 1: never drink, 2: few times/month, 3: 1-2 times/week, or 4: 3+ times/week). In the case of the share of risky 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, but the result does not change. We also regress the risk attitude measure on a full set of age dummies, individual fixed effects and macro variables. Figure C.2A plots the result. It shows a downward sloping pattern of age effects over the life course, similar to Dohmen et al. (2017).

Finally, we control for risk attitudes in the fixed effects estimation (equation 2). Figure C.2B shows that the age effects are virtually identical to our main result in Figure 3B.

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 C.3 shows that the results are similar to our main findings with this specification.



(A) Risk Attitude over the Life Cycle (B) Age Effects, Controlling for Risk Attitudes

Figure C.2: Controlling for Risk Attitude. Panel A plots the values of age dummies in the fixed effects estimation with risk attitude measures as the dependent variable with controlling for macro variables. Panel B plots the values of age dummies in the fixed effects estimation with discount rates as the dependent variable with controlling for risk attitudes and macro variables. The bars indicate 95% confidence intervals.

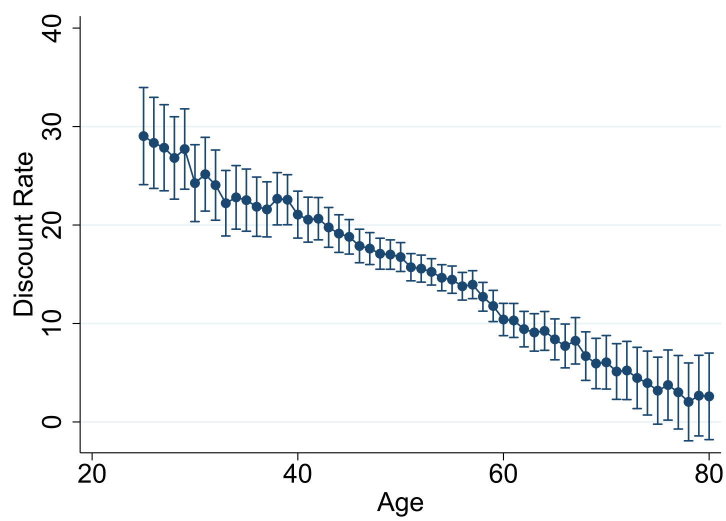


Figure C.3: OLS Estimation. The figure plots the values of age dummies with discount rates as the dependent variable controlling for macro variables and a full set of cohort dummies. The bars indicate 95% confidence intervals.

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