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Temporal discounting in later life

Ellam Kulati [a], Michał Myck [b], Giacomo Pasini [c,d,*]

[a] Centre for Economic Analysis (CenEA), Faculty of Economic Sciences, University of Warsaw, Poland
[b] Centre for Economic Analysis (CenEA, Szczecin), University of Greifswald, IZA-Bonn, Germany
[c] Ca' Foscari University of Venice, Italy
[d] Network for Studies on Pensions, Ageing and Retirement (NETSPAR)

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ABSTRACT

We explore intertemporal decision-making in later life by looking at temporal preference heterogeneity among older individuals. Using choice tasks responses from Poland collected as part of the Survey of Health, Ageing, and Retirement in Europe (SHARE), we elicit individual time preferences using competing discounting specifications. With the formulation that best fits our data, we examine which individual characteristics drive the estimated heterogeneity in later life time preferences. Individual numerical abilities, labour and marital status, as well as household income turn out to be significant correlates of patience. Our analysis also provides methodological guidance for instrument design with the aim of eliciting time preferences in a general survey setting.

1. Introduction

A substantial part of our daily decisions involves an intertemporal dimension. These include the choices concerning saving, human capital investment, employment and retirement, relationships, but also countless daily decisions regarding regular expenditure and consumption. This has stipulated the development of theories of intertemporal decision making and numerous studies on determinants of time preferences and implications of preference heterogeneity in the time dimension. Great strides in understanding such decision processes have been achieved through multidisciplinary advancements, mostly spanning economics, psychology and sociology. They have also relied on data collected in laboratory and field experiments as well as through the use of surveys.

Time discounting — the subjective valuations one puts on receiving money or a good earlier rather than later, also termed time preference or patience — is a fundamental aspect of intertemporal decision-making (Frederick et al., 2002) and empirical studies on patience have sought to understand the determining characteristics behind its observed variation (Croson and Gneezy, 2009; Ersner-Hershfield et al., 2009; Whelan and McHugh, 2009). Analyses have usually been based on laboratory experiments or on studies focused on surveys of smaller sub-samples (Blavatskyy and Maafi, 2018; Castillo et al., 2011; Wang et al., 2016). Moreover, despite the importance of the understanding of how time preferences evolve over the life course, there is surprisingly little evidence regarding intertemporal decisions among older individuals (an important exception is the study by Huffman et al. (2019)). This appears to be a significant gap given the rapid ageing of the population in all developed countries (Bloom and Luca, 2016).

Our analysis seeks to contribute to the understanding of intertemporal decision making by exploring individual time preferences

* Corresponding author.
E-mail address: giacomo.pasini@unive.it (G. Pasini).

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among the older population in Poland using data collected in a study as part of the representative Survey of Health, Ageing, and Retirement in Europe (SHARE). The unique feature of the resources we use is that, unlike in nearly all studies focused on time discounting, our data has not been derived from a controlled lab experiment, but rather was collected in a standard field survey from a large representative sample of older Polish respondents. In a specially designed extensive paper-and-pencil interview individuals were asked to elicit their preferences over receiving specific amounts of money today or in the future. The approach follows Tanaka et al. (2010), and the collected data facilitates estimation of several discounting specifications (exponential, hyperbolic and quasi-hyperbolic).

We find the quasi-hyperbolic discounting formulation to be the most suitable fit of the collected responses, and use this specification to probe whether a set of socioeconomic characteristics can help explain the heterogeneity in the individual time preferences (see Falk et al., 2018). Lower degree of patience is found among rural dwellers, while individuals with higher incomes and numerical cognition seem to be more patient. In spite of some caveats in our findings, due to imposed sampling restrictions, the module design and implementation confirm the feasibility of such studies in the broad survey context, while the identified heterogeneity of preferences points towards the importance of survey-based studies on time preferences as an important avenue to improve our understanding of decisions made in later life.

In Section II we give a brief overview of theory and evidence on the evolution of time discounting over the life course and its determinants. Section III presents the different discounting specifications considered in this study. This is followed by presentation of the data used for this study and the questionnaire design used in the Polish part of the SHARE survey. Results are reported in Section V which is followed by a discussion of our findings, and conclusions.

1.1. *Determinants of time preferences*

Many factors influence individual intertemporal decision making at various stages of life and as people get older factors such as age-related mortality and morbidity hazards gain in importance. The former results in instances where an individual fails to realise any foregone consumption, while the latter diminishes the expected value from any future consumption (Chao et al., 2009; Trostel and Taylor, 2001). A direct age-discounting relationship has been supported in several economic and evolutionary approaches, although the nature of the relationship still remains contentious. A quadratic curve has often been proposed to describe the relationship (Harrison et al., 2002; Richter and Mata, 2018; Sozou and Seymour, 2003) wherein patience is greatest in middle-age with the young and old exhibiting higher levels of impatience. Alternatively, Rogers (1994) posited a positive relation of ageing and patience, while Green et al. (1994) suggested an inverse age-discounting relationship, after discovering lower hyperbolic discount rates among older adults relative to college students, and among college students relative to sixth graders.

However, many empirical studies focused on age specific discounting patterns have focused on younger individuals. They include studies on: children (Castillo et al., 2011), adolescents (Sutter et al., 2013), college or university students (Wang et al., 2016) and non-students (Burks et al., 2009). While a number of studies have been conducted on small representative samples of adults, these usually take the form of field experiments (e.g. Harrison et al. 2002, Meier and Sprenger 2010; Tanaka et al. 2010).

Time preferences have also been shown to relate to health and health-related behavior. Chao et al. (2009) expose a U-shaped relationship between physical health and individual discounting, and higher temporal discounting has been associated with greater mortality (Boyle et al., 2013). Hunter et al. (2018) show that individuals characterized by high discount rates or being present biased – i.e. with susceptibility to the over-pursuit of payoffs closer to the present time (O'Donoghue and Rabin, 2015, 1999) – engage in less physical activity, while Borghans and Golsteyn (2006) find a similar relationship with being overweight and Kang and Ikeda (2014) with smoking.

Existing literature has also highlighted that, similar to risk preferences, context sensitivity, bargaining and the propensity to enter competitive situations (Croson and Gneezy, 2009), time preferences may also differ between men and women. Women have been found to be more apt at deferring gratification, relative to men — even among school-age children (Castillo et al. 2011; Dittrich and Leipold, 2014), and the variation of intertemporal decision making across genders may further be affected by the gender differences in time consistency— changing one's preference as a result of changes in the reference point in time (Frederick et al. 2002; Prince and Shawhan, 2011).

Patience has also been shown to correlate significantly with the level of education. It has been argued that on the one hand, patient individuals forgo immediate labor market opportunities to further their education (Grossman, 2006) while on the other hand, more education encourages a more future oriented perspective among its recipients (Becker and Mulligan, 1997). The latter was further stressed by Ross and Mirowsky (1999), who argued that education improves one's ability to amass and decipher information, and it encourages problem solving thereby granting more control over the events and outcomes of their life. Similarly, cognitive skills – often correlated with education – determine individual perspectives and influence decision making, and have been shown to strongly affect individual economic preferences (Burks et al., 2009) and to positively relate to patience. In empirical studies, however, insignificant effects of education on temporal preferences are not uncommon (Tanaka et al., 2010).

The literature has also explored the correlation of patience and wealth. Theoretical approaches have supposed that the wealthy would discount the future comparably less than their relatively less well-off counterparts (Becker and Mulligan, 1997; Fisher, 1930). While endogeneity of wealth is a significant concern in such studies (Becker and Mulligan, 1997), its inclusion has been empirically supported across studies employing different data and methods, including survey evidence, as well as field and laboratory experiments (Ersner-Hershfield et al., 2009; Lawrance, 1991; Meier and Sprenger, 2010). These results persist even when endowments are artificially controlled to actuate individuals who perceive themselves as poverty-stricken or otherwise (Haushofer et al., 2013), although some studies have failed to find a significant relationship between patience and poverty (Ogaki and Atkeson, 1997).

The unique contribution of this paper is that we test the potential to examine individual time preferences in a context of a standard fieldwork survey, i.e., without the full experimental set-up used in a majority of earlier papers. Additionally, since the SHARE survey focuses on adults aged 50+, the analysis elicits time preference of older individuals, a rapidly growing part of the population in most developed countries. Our survey design builds on the approach used in Tanaka et al. (2010) both in the number of questions asked and the range of relative hypothetical financial outcomes. This significantly extends the estimation potential in comparison to several studies conducted earlier on older Americans, e.g. Boyle et al. (2012), Boyle et al. (2013) and Huffman et al. (2019). Our approach allows us to test a number of different alternative discounting specifications and the rich set of information collected in SHARE facilitates examination of the relationship between time preferences and individual characteristics.

1.2. Formalizing intertemporal decisions

In his seminal work on intertemporal decision making, Samuelson (1937) introduced the discounted utility (DU) model of time-separable utility flows and exponential discounting. A model that condensed intertemporal choice motivations into a discount rate (r) allowing it to be widely accepted and regarded as a germane representation of observed human behavior (Frederick et al., 2002). Further legitimized by Koopmans' (1960) behavioral characterization it dominated as economists' go-to framework for modelling intertemporal choices (Blavatskyy and Maafi, 2018; Cohen et al., 2020).

However, the assumptions founding the DU model have since been extensively tested and mostly found wanting, as chronicled by Frederick et al. (2002). Money earlier or later experiments, comparable to the approach employed in this study, are among the methods used to empirically contradict the model (Cohen et al., 2020). Discovered shortcomings of the DU model incentivised alternate formulations, among them: mental accounting models (Prelec and Loewenstein, 1998; Thaler, 1999), and multiple-self models (Ainslie and Haslam, 1992; Prelec and Loewenstein, 1998). Other DU model alternatives are based on different specifications of the discount function.

In this analysis we are more concerned with the latter. This is because, besides the undisputed role of discounting in intertemporal decision-making, an equally important consideration is what discounting model one ought to adopt (Musau, 2009). Possible alternatives to the exponential discounting are hyperbolic and quasi-hyperbolic discounting specifications, as well as the quasi-hyperbolic formulation with fixed instead of variable present bias costs.

Benhabib et al. (2010) posit that the value of any amount \$y with a delay $(t > 0)$ is $\$yD(y,t)$ where $D(y,\ t)$ is a discount function. The valuation of $\$yD(y,t)$ undergoes exponential, hyperbolic and quasi-hyperbolic discounting, respectively, if:

$$D(y,t) = e^{(-rt)} \textit{ Where } r\ > 0 \textit{ and } t\ > 0 \tag{1}$$

$$D(y,\ t) = \frac{1}{1+rt} \textit{ Where } r\ > 0 \textit{ and } t\ > 0 \tag{2}$$

$$D(y,\ t) = \beta e^{-rt} \textit{ Where } r\ > 0,\ 0 < \beta < 1 \textit{ and } t > 0 \tag{3}$$

These formulations comprise parameters for the discount rate (r), delay time (t) and present bias (β) – the psychological tendency of assigning discrete costs to future rewards, relative to present ones (Benhabib et al., 2010).

The present bias in Eq. (3) takes a variable cost. As highlighted by Benhabib et al. (2010), the amount \$y, when received in the future, is valued as \$y-(1-β) y, which varies with y. The converse of the variable cost specification attaches a fixed cost (b) to the amount \$y when received in the future. The fixed cost formulation takes the form in either Eqs. (4) or (5). The parameter m determines the allocation of the costs over time, resulting in a specification wherein the fixed cost is either discounted (4) or not (5).

$$D(y,\ t) = e^{-rt}(y + be^{-mt}) - b\ =\ D(y,t) = e^{(-rt)} - \left(1 - e^{(-rt)}\right)\frac{b}{y}\ \ if\ \ m = 0 \tag{4}$$

$$D(y,\ t) = e^{-rt} - \frac{b}{y}\ \ if\ m\ = \infty \tag{5}$$

Similar to other behavioural economics approaches, formulations given in Eqs. (2)–(5) attempt to achieve generality by introducing one, two or three additional parameters to the standard approach — Eq. (1), and using the estimated values of the parameters, we can evaluate the behavioural models against each other (Camerer and Loewenstein, 2011).

1.3. Data, sample selection and sensitivity analysis

The Survey of Health, Ageing and Retirement in Europe (SHARE) has held face to face computer-assisted personal interviews (CAPI) with individuals aged 50 or older — along with their partners of varied ages — from 28 European countries, as well as Israel since 2004. As of 2022, the panel study encompasses 8 waves, which include a main questionnaire with modules covering issues ranging from individual health and socio-economic statuses to social networks and support. The interviews in all but wave 3 of SHARE were supplemented with additional self-completed (drop-off) questionnaires which often included country-specific questionnaire items.

Our data is sourced from the 7.1.0 release of the 6th wave of the SHARE panel carried out in 2015 in 18 of the 29 countries (Börsch-Supan, 2019d). As part of the wave 6 interviews, a unique drop-off survey was implemented in Poland, based on the design applied by

Table 1
Completion of the SHARE drop-off questionnaire.

		No. of respondents
Total sample:		1,807
	Main survey only (no drop-off)	220
	Incomplete drop-offs	182
	Completed drop-offs	1,405
Distribution of completed drop-offs:		
	a. Always patient	522
	b. Mixed and consistent	717
	c. Mixed and inconsistent	61
	d. Always impatient	105

Source: Own calculations based on the Polish sample of SHARE wave 6.

Table 2
Complete responses summary statistics.

	Surveys	Mean	Std. Dev.	Minimum	Maximum
Age	1,405	66.600	9.345	50	96
Female	1,405	0.563	0.496	0	1
Years of education	1,405	10.174	3.255	0	23
Number of children	1,405	2.482	1.452	0	13
ln(Income)	1,405	8.727	0.768	4.171	11.884
Verbal fluency (standardized)	1,405	0.031	0.990	-2.650	12.091
Numerically cognizant	1,405	0.712	0.453	0	1
Marital Status	1,405				
Married	1,037	0.738			
Single	102	0.073			
Widowed	266	0.189			
Labour market status	1,405				
Retired	869	0.619			
Employed/self-employed	279	0.199			
Permanently sick/disabled	91	0.065			
Other	166	0.118			
Health	1,405				
Excellent	19	0.014			
Very good	100	0.071			
Good	540	0.384			
Fair	466	0.332			
Poor	280	0.199			
Location	1,405				
Big city	208	0.148			
Suburbs/Outskirts of big city	35	0.025			
Large town	327	0.233			
Small town	155	0.110			
Rural area/Village	680	0.484			

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: ln (Income): Log transformed monthly income; *Verbal fluency* (total score, when a score of 1 is assigned for each animal a respondent lists within 1 minute) is a standardized score; and individuals are numerically *cognizant* when their numeracy score (total score, when a score of 1 is assigned for each of five serial subtractions) is 4 or 5. *Married* includes cohabiting married respondents as well as those living separately. *Single* comprises of divorced respondents and those that have never married. *Other* labour statuses comprise of *homemakers*, the *unemployed* as well as individuals who failed to fall in any of the given categories.

Tanaka et al. (2010). The drop-off presented respondents with 40 hypothetical choice tasks to elicit their time preferences. In the survey, the 1826 Polish respondents who participated in the main CAPI interview were to choose between larger later rewards and smaller immediate rewards expressed in the Polish currency (Polish złoty, PLN) phrased as follows: *Which of the two payments would you prefer? Would you prefer to receive: Option A – y PLN in t days; or Option B – x PLN today*?

Delayed rewards (y) took 4 separate values, 300, 500, 1100 and 1400 PLN (equivalent to approximately 72, 119, 262 and 334 euros respectively).[1] Each delayed amount was given in competition to five incremental options of immediate payoffs (x), creating a total of 40 sets of alternatives. Immediate reward values (x) were arithmetic progressions of 50, 90, 200 and 250 PLN (approximately 12, 21,

[1] The euro-PLN exchange rate on 30.06.2015 was €1= 4.1944 PLN. For reference it is worth noting that the value of monthly gross minimum old-age pension in Poland in 2015 was 844.45 PLN (201.33 euros) (OECD, 2015).

Table 3
Correlates of broad response categories.

	Always patient	Std. Err.	Always impatient	Std. Err.
Age	0.001	0.004	0.001	0.001
Female	0.015	0.025	0.002	0.016
Years of education	-0.016**	0.006	-0.004	0.003
Number of children	0.014	0.010	-0.011	0.008
ln(Income)	0.068***	0.025	-0.031***	0.009
Verbal fluency (standardized)	0.000	0.026	-0.001	0.012
Numerically cognizant	0.070	0.044	-0.003	0.021
Marital status				
Single	0.003	0.052	-0.013	0.025
Widowed	0.099**	0.050	-0.032**	0.016
Labour market status				
Employed/self-employed	0.041	0.066	-0.013	0.023
Permanently sick/disabled	-0.026	0.066	0.011	0.025
Other	-0.088*	0.052	-0.018	0.022
Location				
Rural	-0.015	0.045	-0.021	0.020
Health				
Poor	0.018	0.033	0.004	0.018

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: Marginal effects based on multinomial logit regressions estimates. Total observations: 1405 — 'Always patient' category: 522 observations, 'Always impatient' category: 105 observations; 'Mixed reply' category (778 observations) taken as reference. Significance levels: ***$p>$ 0.01, **$p>$ 0.05, *$p>$ 0.01. Std. Err.: Delta-method standard errors. Numerically cognizant is as defined in Table 2. Reference groups: Marital status: *Married;* Labour market status: *Retired*; Location: residents of *small* and *large towns, big cities* and their *suburbs;* Health: all individuals whose self-perceived health is *excellent, very good, good* or *fair.*

48 and 60 euros), and the waiting periods (t) for the delayed payments were 3 days, 1 week, 2 weeks or 3 months. We provide all 40 choices as presented to the respondents of the survey in Appendix A.

As recorded in Table 1, from the 1,807 Polish respondents of the main CAPI interview aged 50 years and over, the survey yielded 1,587 drop-off responses, of which 1,405 were fully completed. These latter responses are categorised depending on whether the subject always opted for the delayed reward (*always patient*), the immediate reward (*always impatient*) or alternated at least once between the two in the 40 choice tasks (*mixed*). Among the mixed replies, 61 were completed inconsistently judging by preference transitivity ($z > y$ *if* $x > y$ and $\forall\ z > x$).

Capturing temporal preferences of the respondents requires their preference to be within the upper and lower bounds of the choice tasks (Frederick et al., 2002). Thus, while full sample estimation is feasible, our main analysis is limited to respondents who alternated at least once in the given choice tasks. Consequently, only the 717 respondents with mixed responses (Table 1) are used in the main specifications. However, as a robustness check, we provide the summaries of estimations based on the full sample of 1,344 subjects with consistent responses in Appendix E. Although this sample selection does not affect the choice of the most preferred discounting model, specific correlates of the discounting parameters are sensitive to this change. Therefore, we advise the exercise of caution when generalizing the results from the restricted sample.

The time preference data collected in the drop-off questionnaire has been combined with socioeconomic variables sourced from the wave 6 of SHARE and complemented with additional information from waves 2, 3, 4 and 7 where necessary (Börsch-Supan, 2022, 2020, 2019b, 2019c, 2019a). A brief summary of the variables is provided in Table 2, with additional summaries and details given in Appendix B.

The socio-economic characteristics include information on gender, age, education and monthly household income, as well as current employment and marital status, number of children, location and self-perceived health. SHARE also provides information on cognition from which we include two different measures: verbal fluency and numeracy. Verbal fluency provides a measure of executive functions by requiring respondents to name as many animals as possible within a minute (Ahmed et al., 2018; Paula et al., 2015). We standardise the verbal fluency scores following Ahmed et al. (2018). Numeracy contains scores from five serial subtractions of seven from a starting value of 100. We delineate numerically cognizant respondents by dichotomizing numeracy into those with numeracy scores of 4 and 5 or otherwise (Barbosa et al., 2021; Schneeweis et al., 2014).

Although majority of the respondents were in their 60s, 341 participants in the sample were aged below 60 years, and 298 respondents were aged 75 or over. The sample is also characterized by relatively greater proportions of women (56.3%), married respondents (73.8%), retirees (61.9%) and rural dwellers (48.4%). The statistics also highlight that a non-negligible portion of the

Table 4
Probability estimates of response consistency.

	Coefficient	Std. Err.
Constant	0.754**	0.326
Age	0.006	0.009
Age^2	0.000	0.000
Female	-0.013	0.011
Years of education	-0.001	0.001
Number of children	0.002	0.003
ln(Income)	-0.006	0.008
Verbal fluency (standardized)	-0.001	0.007
Numerically cognizant	-0.002	0.019
Marital status		
Single	0.033**	0.014
Widowed	0.008	0.015
Labour market status		
Employed/self-employed	0.048*	0.025
Permanently sick/disabled	0.001	0.021
Other	-0.023	0.022
Location		
Rural	-0.008	0.012
Health		
Poor	-0.001	0.012
Respondents	1,418	
Prob > F	0.015	
R^2	0.022	

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: Results of linear probability model with consistency (=1) as the dependent variable. Marginal effect of age: 0.002*. Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01. Std. Err.: Robust standard errors. Numerically cognizant is as defined in Table 2. Reference groups for *Marital Status, Labour Market Status Health,* and *Location* are as stated in Table 3.

sample resides in urban areas—a big city, large or small town. The Polish SHARE sample is further characterised by low numbers of individuals with excellent self-rated health (1.4%) and a sizeable share of widowed respondents (18.9%).

Before delving into the details of estimating the specific parameters of the utility function discussed in Section III, we first explore the variation across the response types specified in Table 1.[2] For this purpose, we examine the distinguishing features of individuals whose responses categorised them broadly as — *always patient, mixed* or *always impatient* – using a multinomial logistic regression. The marginal effects of the multinomial logistic analysis are presented in Table 3, with coefficient estimates provided in Appendix C. Few of the examined characteristics are significantly correlated with the probability of being in either of the *always patient* or *always impatient* categories. The results show that an additional year of education reduces the average probability of always being patient by 0.016 percentage points. Higher household income increases the average probability of being always patient and consistently reduces that of being always impatient. Relative to being in the *'mixed reply'* category, widowed respondents are more likely than those who are married to be '*always patient*' and less likely to be '*always impatient*'. Lastly, compared to retirees, respondents with an '*other*' labour market status are marginally less likely to be '*always patient*'.

Since our final estimation sample excludes the 61 individuals with inconsistent answers (see Table 1), we further examine if there are any characteristics which made the respondents more or less likely to fall into this category. We thus group all complete responses as consistent or otherwise and examine the probability of giving an inconsistent set of replies. As shown in Table 4, majority of individual characteristics are not significantly related to inconsistency in the replies. (Self-) employed respondents and single respondents are shown to be marginally more likely to provide consistent responses, relative to retirees and married subjects respectively.

Ultimately, to measure the time discounting of the survey respondents, we limit our analysis to the 717 respondents who gave complete, mixed and consistent responses. As presented in Table 4 there is little regularity with respect to inconsistency of answers given in the survey. However, given the patterns identified from the point of view of declared patience, we need to bear in mind the likely bias resulting from the uncovered patterns in the sample classification, particularly with regard to income and marital status (Table 3). An important lesson from the conducted exercise for any future application of similar question modules in surveys is to cover a broader range of monetary response categories to maximize the proportion of *mixed replies*.

[2] An unreported analysis of drop-off completion only finds greater numerical cognition and rural dwelling (relative to residents of *small* and *large towns, big cities* and their *suburbs)* to significantly affect completion (increasing its likelihood), with the latter having only a marginally significant effect.

Table 5
Estimates of discounting models.

	Exponential	Hyperbolic	Quasi-Hyperbolic	Quasi-Hyperbolic (UFC)	Quasi-Hyperbolic (DFC)
μ (noise parameter)	0.006***	0.006***	0.008***	0.007***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R (discount rate)	0.005***	0.007***	0.003***	0.004***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Β (variable pr. bias)			0.871***		
			(0.008)		
B (fixed pr. bias)				39.116***	-69.668**
				(6.050)	(28.768)
Observations	28,680	28,680	28,680	28,680	28,680
Respondents	717	717	717	717	717
Log-likelihood	-15260.48	-15193.19	-14825.98	-15211.98	-15256.13
Adjusted-R^2	0.425	0.428	0.442	0.427	0.425
AIC	30524.97	30390.37	29657.97	30429.95	30518.26
BIC	30541.5	30406.9	29682.76	30454.74	30543.05

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: Non-linear least squares estimates. Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01. Robust standard errors are in parentheses. UFC: Undiscounted fixed cost present bias; DFC: Discounted fixed cost present bias; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion. Wilcoxon signed rank tests confirm significant differences between the formulations (see appendix D).

Table 6
Time preference heterogeneity estimates.

	β (variable pr. bias)	Robust Std. Err.	*r* *(discount rate)*	Robust Std. Err.
μ (noise parameter)	0.008***	0.000		
Constant	1.006**	0.469	1.651**	0.733
Age	-0.006	0.013	-0.030	0.020
Age^2	0.000	0.000	0.000	0.000
Female	-0.018	0.017	-0.017	0.027
Years of education	-0.006*	0.003	0.005	0.006
Number of children	0.002	0.006	-0.011	0.011
ln(Income)	0.022*	0.012	-0.023	0.018
Verbal fluency (standardized)	0.010	0.010	0.003	0.012
Numerically cognizant	-0.029	0.020	-0.083***	0.031
Marital status				
Single	0.042	0.032	0.005	0.051
Widowed	-0.048*	0.026	-0.047	0.039
Labour market status				
Employed/self-employed	0.028	0.028	-0.084**	0.043
Permanently sick/disabled	-0.040	0.037	-0.159***	0.054
Other	-0.036	0.029	0.016	0.043
Location				
Rural	0.020	0.018	0.054*	0.028
Health				
Poor	-0.021	0.022	0.024	0.038
Observations	28,680			
Respondents	717			
Adjusted-R^2	0.449			
Log-Likelihood	-14651.14			
AIC	29368.28			
BIC	29640.99			

Source: Own calculations based on the Polish sample of SHARE.
Notes: Estimates from a logistic regression of the probability of choosing a delayed reward (y) in t days over an immediate one (x); P-value of overall significance of age on discount rate (present bias): 0.286 (0.722). Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01. Std. Err.: Standard error; *μ:* noise parameter. Discount rate (*r*) estimates are scaled— multiplied by 100. Numerically cognizant is as defined in Table 2. Reference groups for *Marital Status, Labour Market Status Health,* and *Location* are as stated in Table 3.

1.4. Temporal discounting: results

To aid the comparison of the different discounting specifications, we adopt Benhabib *et al.'s* (2010) 4-parameter specification nesting the competing forms. The model designates a current value of $y\beta(1-(1-\theta)rt)^{\frac{1}{1-\theta}}-b$ for any reward (y) to be received at a

Table B
Category distributions of surveys.

	Complete Responses	Consistent responses	Always Patient	Mixed Responses	Always impatient
Age	1,405	1,344	522	717	105
Female	1,405	1,344	522	717	105
Years of Education	1,405	1,344	522	717	105
Number of children	1,405	1,344	522	717	105
ln(Income)	1,405	1,344	522	717	105
Verbal fluency	1,405	1,344	522	717	105
Numeracy	1,405	1,344	522	717	105
0 subtractions	66	65	32	29	4
1 subtraction	93	90	34	42	14
2 subtractions	72	71	30	36	5
3 subtractions	156	146	39	95	12
4 subtractions	234	224	79	129	16
5 subtractions	767	731	301	376	54
Refusal	17	17	7	10	-
Marital Status	1,405	1,344	522	717	105
Married	1,037	987	375	536	76
Single	102	100	29	61	10
Widowed	266	257	118	120	19
Labour market status	1,405	1,344	522	717	105
Retired	869	833	345	417	71
Employed/self-employed	279	272	104	153	15
Permanently sick/disabled	91	86	29	49	8
Other	166	153	44	98	11
Health	1,405	1,344	522	717	105
Excellent	19	19	7	10	2
Very good	100	97	45	45	7
Good	540	510	166	302	42
Fair	466	449	191	228	30
Poor	280	269	113	132	24
Location	1,405	1,344	522	717	105
Big city	208	198	77	102	19
Suburbs/Outskirts of big city	35	33	7	21	5
Large town	327	313	122	165	26
Small town	155	150	59	83	8
Rural area/Village	680	650	257	346	47

Source: Own calculations based on the Polish sample of SHARE wave 6.

delay $(t > 0)$. In this formulation the parameters permit one to disentangle the discount rate (r), hyperbolicity (θ), or the curvature of the discount function, and both variable (β) and fixed cost (b) components of present bias.

The specification reduces to: exponential discounting (e^{-rt}), when $\beta = 1$, $b = 0$ and θ approaches its limit (=1)*;* hyperbolic discounting when $\beta = 1$, $b = 0$ and $\theta = 2$; traditional quasi-hyperbolic (βe^{-rt}), wherein the present bias cost is variable, when $\theta = 1$, $b = 0$ and β is unconstrained; and a quasi-hyperbolic specification with a fixed present bias cost $(e^{-rt} - b)$ when only $\theta = 1$ and $\beta = 0$ (Benhabib et al., 2010). The latter comprises of a specification with a discounted (DFC) or undiscounted fixed cost (UFC) present bias. As stipulated by Benhabib, et al. (2010), we deal with a variable present bias if $\beta < 1$, and with a fixed cost whenever $b > 0$.

Similar to Tanaka et al. (2010), we presume that the probability of choosing an immediate reward (x) over a delayed one (y), in t days, can be represented by the logistic function:

$$P(x > (y,t)) = \frac{1}{1 + \exp\left[-\mu\left(x - y\left(\beta(1-(1-\theta)rt)^{\frac{1}{1-\theta}} - b\right)\right)\right]} \tag{6}$$

with (μ) representing a noise parameter. Estimations of this function and its reductions have been carried out using non-linear least squares. The fully flexible specification with an unrestricted θ parameter could not be estimated on our sample, and our results comprise estimates of parameters of its five reductions, which are presented in Table 5.

Looking at the fit of the estimated models, the log-likelihood, adjusted-R^2, AIC and BIC statistics confirm that the quasi-hyperbolic specification offers a better fit relative to the other four, which is also confirmed by Wilcoxon signed rank tests (see Appendix D). An F-test, performed under the traditional quasi-hyperbolic formulation, also rejects the restriction that $\beta = 1$, which characterizes both exponential and hyperbolic specifications. This suggests that the traditional quasi-hyperbolic discounting specification seems to be the best discounting formulation for our sample.

The present bias (β=0.871) and daily discounting (r=0.003) estimates provided by the preferred traditional quasi-hyperbolic specification imply that 796 PLN today would entice the respondents to forego 1000 PLN in a month. Whelan and McHugh (2009)

Table C
Multinomial logistic regression of complete responses

	Always patient	Robust Std. Err.	Always impatient	Robust Std. Err.
Constant	-1.948	4.927	-1.169	5.480
Age	-0.017	0.139	0.095	0.149
Age^2	0.000	0.001	-0.001	0.001
Female	0.073	0.109	0.063	0.239
Years of education	-0.081***	0.031	-0.096**	0.044
Number of children	0.046	0.044	-0.145	0.121
ln(Income)	0.261**	0.117	-0.358**	0.144
Verbal fluency (standardized)	0.001	0.114	-0.009	0.171
Numerically cognizant	0.323*	0.192	0.090	0.305
Marital status				
Single	-0.009	0.244	-0.189	0.398
Widowed	0.386*	0.216	-0.362	0.266
Labour market status				
Employed/self-employed	0.164	0.289	-0.127	0.377
Permanently sick/disabled	-0.102	0.304	0.112	0.320
Other	-0.459*	0.259	-0.444	0.390
Location				
Rural area/Village	-0.111	0.197	-0.359	0.267
Health				
Poor Health	0.091	0.158	0.093	0.283
Respondents	1,405			
Log-pseudo-likelihood	-1211.350			
Chi^2 p-value	0.000			
Pseudo R^2	0.030			

Source: Own calculations based on the Polish sample of SHARE wave 6.

Table D
Wilcoxon signed rank test of discounting specifications.

	Exponential	Hyperbolic	Quasi-Hyperbolic	Quasi-Hyperbolic (UFC)
Exponential	–			
Hyperbolic	3.011***	–		
Quasi-Hyperbolic	7.529***	-4.770***	–	
Quasi-Hyperbolic (UFC)	3.513***	-4.268***	18.073***	–
Quasi-Hyperbolic (DFC)	49.199***	-9.286***	-7.529***	-7.529***

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: Null hypothesis: Equivalent residuals. Wilcoxon signed rank test z-statistics are provided. Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01.

reveal exponential discount rate estimates of 10 older adults (mean age=73; standard deviation=4.12) between 0.087 and 0.118, over delay horizons ranging from 1 day to 1 year. Additionally, a study of 406 older persons by Boyle et al. (2013) reports lower annual hyperbolic discounting rates ranging from 8% to 90%. However, temporal preferences therein are based on 3, in contrast to our 40, choice tasks, and are characterized by a larger delay horizon—a year. Moreover, the disparities may be attributed to cultural and developmental differences between the respective respondents (Rieger et al., 2021; Wang et al., 2016). Our estimates also overshoot the exponential discounting estimates obtained by Huffman et al. (2019), in their study of individuals over the age of 70. A separate study of 388 community dwelling older persons however reveals comparable hyperbolic discount rate estimates — between 0.002 and 0.086 — over a delay horizon of 1 month (Boyle et al. 2012).

With the traditional quasi-hyperbolic discounting specification which performs best among the estimated models, we conduct an additional nonlinear least squares estimation, permitting both the discount rate (r) and present bias (β) to be linear functions of the socioeconomic variables (X). The specification estimated is given in Eq. (7) and its results are provided in Table 6.

$$P(x > (y,t)) = \frac{1}{1 + \exp[-\mu(x - y\beta\exp(-rt))]},$$

$$\text{where } r = \sum_0^n r_i X \text{ and } \beta = \sum_0^n \beta_i X \tag{7}$$

In the estimation we control for the same characteristics as in the analysis of correlates of the broad response categories. It is important to note that lower r values reflect increased patience, while higher β values corresponds to lower present bias, consequently indicating higher patience.

In contrast to Tanaka et al. (2010), but in line with other recent studies (Meier and Sprenger, 2010; O'Donoghue and Rabin, 2015),

Table E. 1
Estimates of discounting models.

	Exponential	Hyperbolic	Quasi-Hyperbolic	Quasi-Hyperbolic (UFC)	Quasi-Hyperbolic (DFC)
μ	0.005***	0.005***	0.005***	0.002***	0.005***
(noise parameter)					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r	0.002***	0.002***	0.002***	0.005***	0.004***
(discount rate)					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β			1.003***		
(variable pr. bias)					
			(0.009)		
b				-278.594***	-414.937***
(fixed pr. bias)					
				(20.713)	(27.154)
Observations	53,760	53,760	53,760	53,760	53,760
Respondents	1,344	1,344	1,344	1,344	1,344
Log-likelihood	-29344.50	-29342.48	-29344.31	-28689.99	-29258.16
Adjusted-R^2	0.260	0.260	0.260	0.278	0.262
AIC	58693.00	58688.96	58694.62	57385.99	58522.31
BIC	58710.79	58706.75	58721.3	57412.66	58548.99

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: Non-linear least squares estimates. Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01. Robust standard errors are in parentheses. UFC: Undiscounted fixed cost present bias; DFC: Discounted fixed cost present bias; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion. Wilcoxon signed rank tests confirm significant differences between the formulations.

Table E. 2
Wilcoxon signed rank test of discounting specifications.

	Exponential	Hyperbolic	Quasi-Hyperbolic	Quasi-Hyperbolic (UFC)
Exponential	–			
Hyperbolic	-36.397***	–		
Quasi-Hyperbolic	33.134***	31.126***	–	
Quasi-Hyperbolic (UFC)	5.021***	5.523***	89.110***	–
Quasi-Hyperbolic (DFC)	88.106***	86.600***	4.518***	6.024***

Source: Own calculations based on the Polish sample of SHARE wave 6.
Notes: Null hypothesis: Equivalent residuals. Wilcoxon signed rank test z-statistics are provided. Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01.

we find that the included socioeconomic variables explain some of the heterogeneity of individual present bias (β).

For instance, one's education duration, being widowed and the income available to the household, are statistically significant correlates of present bias. Specifically, widowed respondents exhibit lower patience via the present bias, relative to their married counterparts. Income constitutes a further positive correlate of patience through the temporal preference parameter. Conversely, more years of education are shown to accompany greater present bias.

Importantly, those with greater numerical competency display greater patience through a lower discount rate (*r*). Likewise, evident from discount rate (*r*) estimates, the (self-) employed and permanently sick or disabled individuals are more likely to be patient than retirees. Finally, the residence location of respondents is revealed to be associated to their temporal preferences, with rural dwellers relatively less likely to defer gratification.

1.5. Discussion and conclusion

The understanding of factors determining how older people approach intertemporal choices has become increasingly important from a policy perspective given the rapid ageing of the population across many countries, and the role intertemporal decision making can play in shaping the evolution of their well-being. Intertemporal decision making among this demographic group can have significant economic and welfare implications (Huffman et al., 2019). Coupling this with the need for greater understanding of individual preference heterogeneity, as suggested by Falk et al. (2018), forms the background of the investigation presented in this paper.

We use responses to choice tasks presented to Polish respondents, aged 50 years or older (and their partners), as part of wave 6 of the SHARE survey to estimate individual time preferences using various discounting specifications. The traditional quasi-hyperbolic formulation of discounting turns out to fit our responses better than the exponential and hyperbolic discounting forms, as well as the quasi-hyperbolic formulations with fixed cost present bias posited by Benhabib et al. (2010). However, unlike Akin and Yavas (2007), we find support for the fixed cost present bias specification of the quasi-hyperbolic discounting.

Using the traditional quasi hyperbolic specification, we further investigate the extent to which different socioeconomic characteristics can explain the heterogeneity in individual discount rate and present bias estimates. In contrast to Tanaka et al. (2010), our socioeconomic variables significantly correlate with both the present-bias and discount rates. The results highlight significant

Table E. 3
Time preference heterogeneity estimates.

	β (variable pr. bias)	Robust Std. Err.	*r* *(discount rate)*	Robust Std. Err.
μ (noise parameter)	0.005***	0.000		
Constant	0.811	0.716	1.061**	0.534
Age	-0.013	0.019	-0.014	0.014
Age^2	0.000	0.000	0.000	0.000
Female	0.009	0.027	-0.010	0.020
Years of education	-0.012**	0.005	0.005	0.004
Number of children	0.020**	0.010	-0.005	0.008
ln(Income)	0.079***	0.020	-0.031*	0.016
Verbal fluency (standardized)	0.031*	0.017	0.026**	0.012
Numerically cognizant	0.020	0.031	-0.066***	0.024
Marital status				
Single	0.053	0.052	0.017	0.043
Widowed	0.047	0.037	-0.076***	0.026
Labour market status				
Employed/self-employed	0.072	0.047	-0.005	0.033
Permanently sick/disabled	-0.055	0.055	-0.094**	0.041
Other	-0.053	0.043	0.063*	0.035
Location				
Rural	0.044	0.028	0.054**	0.022
Health				
Poor	-0.008	0.034	0.003	0.025
Observations	53760			
Respondents	1,344			
Adjusted-R^2	0.272			
Log-Likelihood	-28891.41			
AIC	57848.82			
BIC	58142.26			

Source: Own calculations based on the Polish sample of SHARE.
Notes: Estimates from a logistic regression of the probability of choosing a delayed reward (y) in t days over an immediate one (x); P-value of overall significance of age on discount rate (present bias): 0.411 (0.758). Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01. Std. Err.: Standard error; *μ:* noise parameter. Discount rate (*r*) estimates are scaled— multiplied by 100. Definition of *numerically cognizant* and reference groups for *Marital Status, Labour Market Status Health,* and *Location* are as stated in Table C.

relationships between the time preference parameters and numerical abilities, household income and whether the respondent is (self-) employed or permanently sick or disabled. As in several other studies, our results confirm a positive income-patience relationship. However, we fail to find any significant effect of age on the temporal preference heterogeneity of our respondents, either via the present bias or discount rate. It is pertinent to note that since our results are only based on a subsample of respondents, who can be identified in the survey to be within the upper and lower bounds of the choice tasks, the identified correlations with individual characteristics ought to be treated with caution.

Our paper provides several important implications for survey methodology from the point of view of evaluation of discounting. First, we show that it is possible to elicit flexible formulations of time preferences with data based on a relatively short and simple survey module. Given the importance of time discounting in economic modelling and in understanding of individual decision making, the Polish SHARE drop-off questionnaire can act as a reference point for development of survey instruments used in the identification of time preferences in representative samples. Second, we note that in order to account for a broad range of time preferences, the design of the survey instruments ought to carefully consider the range of options presented to the respondents to ensure that they fall within the upper and lower bounds of the choice tasks. Finally, we find a number of statistically significant relations of discounting with socio-demographic characteristics. This, despite the limitations of this study, further stresses the importance of examining time preferences on the basis of representative survey data rather than in lab or field experiments, which are usually carried out on relatively homogenous samples.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

This article is based on data from the Survey of Health, Ageing and Retirement in Europe (SHARE) which is freely available to the research community. See the Acknowledgements section for details. Files facilitating replication of results can be found in the ZENODO repository under: DOI number: 10.5281/zenodo.8143798.

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Appendix

Appendix A: Choice tasks presented in the Polish drop-off questionnaire, SHARE wave 6

Similar to earlier waves of SHARE, the main questionnaire in wave 6 was supplemented with a drop-off survey. Supplementary questionnaires of this kind may be used to collect data on common between- or within-country themes of research interest. The former entails supplying surveys with identical questions to all respondents, regardless of their country of interview. The latter offers opportunities to address country specific research questions— exposing respondents of at least one country to unique questions.

Under wave 6 a country unique survey was supplied to Polish respondents. The questionnaire contained questions on pensions, time preferences, risk, gender and age. Forty choice tasks constituted the time preference elicitation used in the survey. A simple instruction preceded each group of choice tasks asked in questions numbered 6 though 13 ($k.1 - k.5,\ where\ k = 6, \ldots, 13$) as indicated below.

6) Please tick one box (A or B) for each part of the question (6.1 — 6.5).
Which of the two payments would you prefer? Do you prefer to receive...

6.1	500 PLN in one week	☐ A	OR	90 PLN today	☐ B
6.2	500 PLN in one week	☐ A	OR	180 PLN today	☐ B
6.3	500 PLN in one week	☐ A	OR	270 PLN today	☐ B
6.4	500 PLN in one week	☐ A	OR	360 PLN today	☐ B
6.5	500 PLN in one week	☐ A	OR	450 PLN today	☐ B

7) Please tick one box (A or B) for each part of the question (7.1 — 7.5).
Which of the two payments would you prefer? Do you prefer to receive...

7.1	500 PLN in three months	☐ A	OR	90 PLN today	☐ B
7.2	500 PLN in three months	☐ A	OR	180 PLN today	☐ B
7.3	500 PLN in three months	☐ A	OR	270 PLN today	☐ B
7.4	500 PLN in three months	☐ A	OR	360 PLN today	☐ B
7.5	500 PLN in three months	☐ A	OR	450 PLN today	☐ B

8) Please tick one box (A or B) for each part of the question (8.1 — 8.5).
Which of the two payments would you prefer? Do you prefer to receive...

8.1	1400 PLN in one week	☐ A	OR	250 PLN today	☐ B
8.2	1400 PLN in one week	☐ A	OR	500 PLN today	☐ B
8.3	1400 PLN in one week	☐ A	OR	750 PLN today	☐ B
8.4	1400 PLN in one week	☐ A	OR	1000 PLN today	☐ B
8.5	1400 PLN in one week	☐ A	OR	1250 PLN today	☐ B

9) Please tick one box (A or B) for each part of the question (9.1 — 9.5).
Which of the two payments would you prefer? Do you prefer to receive...

9.1	1400 PLN in three months	☐ A	OR	250 PLN today	☐ B
9.2	1400 PLN in three months	☐ A	OR	500 PLN today	☐ B
9.3	1400 PLN in three months	☐ A	OR	750 PLN today	☐ B
9.4	1400 PLN in three months	☐ A	OR	1000 PLN today	☐ B
9.5	1400 PLN in three months	☐ A	OR	1250 PLN today	☐ B

10) Please tick one box (A or B) for each part of the question (10.1 — 10.5).
Which of the two payments would you prefer? Do you prefer to receive…

10.1	1100 PLN in three days	☐ A	OR	200 PLN today	☐ B
10.2	1100 PLN in three days	☐ A	OR	400 PLN today	☐ B
10.3	1100 PLN in three days	☐ A	OR	600 PLN today	☐ B
10.4	1100 PLN in three days	☐ A	OR	800 PLN today	☐ B
10.5	1100 PLN in three days	☐ A	OR	1000 PLN today	☐ B

11) Please tick one box (A or B) for each part of the question (11.1 — 11.5).
Which of the two payments would you prefer? Do you prefer to receive…

11.1	1100 PLN in two weeks	☐ A	OR	200 PLN today	☐ B
11.2	1100 PLN in two weeks	☐ A	OR	400 PLN today	☐ B
11.3	1100 PLN in two weeks	☐ A	OR	600 PLN today	☐ B
11.4	1100 PLN in two weeks	☐ A	OR	800 PLN today	☐ B
11.5	1100 PLN in two weeks	☐ A	OR	1000 PLN today	☐ B

12) Please tick one box (A or B) for each part of the question (12.1 — 12.5).
Which of the two payments would you prefer? Do you prefer to receive…

12.1	300 PLN in three days	☐ A	OR	50 PLN today	☐ B
12.2	300 PLN in three days	☐ A	OR	100 PLN today	☐ B
12.3	300 PLN in three days	☐ A	OR	150 PLN today	☐ B
12.4	300 PLN in three days	☐ A	OR	200 PLN today	☐ B
12.5	300 PLN in three days	☐ A	OR	250 PLN today	☐ B

13) Please tick one box (A or B) for each part of the question (13.1 — 13.5).
Which of the two payments would you prefer? Do you prefer to receive…

13.1	300 PLN in two weeks	☐ A	OR	50 PLN today	☐ B
13.2	300 PLN in two weeks	☐ A	OR	100 PLN today	☐ B
13.3	300 PLN in two weeks	☐ A	OR	150 PLN today	☐ B
13.4	300 PLN in two weeks	☐ A	OR	200 PLN today	☐ B
13.5	300 PLN in two weeks	☐ A	OR	250 PLN today	☐ B

Appendix B: Summary of variables

Table B

Table B indicates the distribution of the survey responses, wherein the final numeracy score assigns one point for each correct subtraction. The score only penalizes participants for errors made in the first subtraction— if the first subtraction is not 93 the maximum numeracy score achievable is 4. All consequent responses to the numerical test are deemed correct if the difference of consecutive subtractions is seven. Regardless of completion of the numeracy test, attempting more than the first subtraction allows categorization according to how many of the five subtractions are done successfully. The verbal fluency measure allocates a point for each correctly named animal within the 1-minute time limit.

The monthly household incomes, whose logarithmic transformations (*ln(income)*) are used in the analysis — are total income values generated by aggregating specific income components reported in the survey (see *thinc*: SHARE, 2020). Of the 6 respondents who reported zero income in each category, we use information from a separate overall household income question (see *thinc2*: SHARE, 2020). The final income variable comprises 1,051 values for which all necessary information was reported by respondents and 367 values wherein at least one of the aggregated components needed to be imputed (for details of imputation procedures see: SHARE, 2020).

The different categories of the categorical variables — marital status, labour market status, health, and location — and their distributions under the different groupings are also provided in Table B. Finally, out of the location and health variables we generate the poor self-perceived health (*phealth=1*) and rural dwelling (*rural=1*) dummies used in the analyses.

Appendix C: Regression results of complete responses to the discounting module

A multinomial logistic analysis is conducted to analyse whether any of the included socioeconomic variables can explain the likelihood of respondents' time preferences being outside, relative to within, the bounds of the choice tasks. The results are presented in Table C below.

Notes: Mixed reply category (787 Observations) is taken as reference—always patient: 526 observations and always impatient: 105 observations. Significance levels: ***p> 0.01, **p> 0.05, *p> 0.01. Std. Err.: Robust standard error. Individuals are numerically *cognizant* when their numeracy score (total score, when a score of 1 is assigned for each of five serial subtractions) is 4 or 5. Reference groups: Marital status: *Married,* Labour market status: *Retired*, Location: residents of *small* and *large towns, big cities* and their *suburbs;* and Health: Individuals whose self-perceived health is *excellent, very good, good* and *fair*.

Appendix D: Tests of discounting formulation differences

Residuals from the different discounting formulations used in Table 5 fail to satisfy the normality prerequisite required to contrast them using paired t-tests. Consequently, we employ its non-parametric alternative, the Wilcoxon signed rank test, to test whether there is a significant difference between the different discounting formulations. The test of residuals reports significant differences in all discounting formulations residuals Table D.

Appendix E: Robustness checks: estimations on the full consistent sample

To test sensitivity of results to the exclusion of the '*always patient*' and '*always impatient*' categories we re-run the estimations using the full sample of respondents who provided consistent replies. We begin by investigating the most preferred model for the data as shown in Table E. 1 below.

The traditional quasi hyperbolic formulation remains the most preferred discounting specification even after the inclusion of respondents at both ends of our time preference spectrum— adjudged by the provided information criteria. The inclusion of the '*always patient*' and '*always impatient*' individuals has an equalizing effect on the noise and discount rate parameters. Conversely, the change masks previously found present-bias both via the parameter's variable and fixed cost specifications. Despite these changes, the discounting formulations remain significantly different as reported in Table E. 2 below.

Disaggregating the time preference parameters in the preferred quasi-hyperbolic specification, based on individual socioeconomic traits we obtain the results in Table E3 below. The estimates show education duration to be inversely related to patience, with household income and the number of children one has increasing the likelihood of deferring gratification, via the present bias. Furthermore, according to the discount rate estimates, numerically cognizant respondents, as well as those from higher income households are more patient. Widowed respondents and those categorized as permanently sick or disabled are also shown to be more patient, relative to married subjects and retirees, respectively. Those in the '*other*' labour market status are further shown to be less likely to be patient than retirees. Finally, the overall effect of verbal fluency in the results is ambiguous—associated with greater patience via the present bias parameter, and inversely correlated to patience via the discount rate Table E. 3.

References

Ahmed, R., Kesavayuth, D., Zikos, V., 2018. Does being smarter make you happier? Evidence from Europe. J. Behav. Exp. Econ. 76, 55–67. https://doi.org/10.1016/j.socec.2018.06.004.

Ainslie, G., Haslam, N., 1992. Hyperbolic Discounting, In: Choice Over Time. Russell Sage Foundation, New York, NY, US, pp. 57–92.

Barbosa, R., Midão, L., Almada, M., Costa, E., 2021. Cognitive performance in older adults across Europe based on the SHARE database. Aging. Neuropsychol. Cogn. 28, 584–599. https://doi.org/10.1080/13825585.2020.1799927.

Becker, G.S., Mulligan, C.B., 1997. The endogenous determination of time preference. Q. J. Econ. 112, 729–758. https://doi.org/10.1162/003355397555334.

Benhabib, J., Bisin, A., Schotter, A., 2010. Present-bias, quasi-hyperbolic discounting, and fixed costs. Games Econ. Behav. 69, 205–223. https://doi.org/10.1016/j.geb.2009.11.003.

Blavatskyy, P.R., Maafi, H., 2018. Estimating representations of time preferences and models of probabilistic intertemporal choice on experimental data. J. Risk Uncertain. 56, 259–287. https://doi.org/10.1007/s11166-018-9281-7.

Bloom, D.E., Luca, D.L., Piggott, J., Woodland, A., 2016. The global demography of aging: facts, explanations, future. Handbook of the Economics of Population Aging. North-Holland, Oxford, pp. 3–56. https://doi.org/10.1016/bs.hespa.2016.06.002.

Borghans, L., Golsteyn, B.H.H., 2006. Time discounting and the body mass index: evidence from the Netherlands. Econ. Hum. Biol. 4, 39–61. https://doi.org/10.1016/j.ehb.2005.10.001.

Börsch-Supan, A., 2022. Survey of health, ageing and retirement in Europe (SHARE) Wave 3 – SHARELIFE., Release version: 8.0.0. SHARE-ERIC. Data Set. doi: 10.6103/SHARE.w1.800.

Börsch-Supan, A., 2020. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 7. Release version: 7.1.1. SHARE-ERIC. Data set.

Börsch-Supan, A., 2019 Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 6. Release version: 7.1.0. SHARE-ERIC. Data set.

Börsch-Supan, A., 2019. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 2. Release version: 7.1.0. SHARE-ERIC. Data set.

Börsch-Supan, A., 2019. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 4. Release version: 7.1.0. SHARE-ERIC. Data set.

Börsch-Supan, A., Brandt, M., Hunkler, C., Kneip, T., Korbmacher, J., Malter, F., Schaan, B., Stuck, S., Zuber, S., 2013. Data resource profile: the survey of health, ageing and retirement in Europe (SHARE). Int. J. Epidemiol. 42, 992–1001. https://doi.org/10.1093/ije/dyt088.

Boyle, P.A., Yu, L., Gamble, K.J., Bennett, D.A., 2013. Temporal discounting is associated with an increased risk of mortality among community-based older persons without dementia. PLoS One 8, 1–5. https://doi.org/10.1371/journal.pone.0067376.

Boyle, P.A., Yu, L., Segawa, E., Wilson, R.S., Buchman, A.S., Laibson, D.I., Bennett, D.A., 2012. Association of cognition with temporal discounting in community based older persons. BMC Geriatr. 12, 1–7. https://doi.org/10.1186/1471-2318-12-48.

Burks, S.V., Carpenter, J.P., Goette, L., Rustichini, A., 2009. Cognitive skills affect economic preferences, strategic behavior, and job attachment. PNAS 106, 7745–7750. https://doi.org/10.1073/pnas.0812360106.

Camerer, C.F., Loewenstein, G. Camerer, C.F., Loewenstein, G., Rabin, M., 2011. Behavioral economics: past, present and future. Advances in Behavioral Economics. Princeton University Press, New Jersey, pp. 3–51. https://doi.org/10.2307/j.ctvcm4j8j.

Castillo, M., Ferraro, P.J., Jordan, J.L., Petrie, R., 2011. The today and tomorrow of kids: Time preferences and educational outcomes of children. J. Public Econ. 95, 1377–1385. https://doi.org/10.1016/j.jpubeco.2011.07.009.
Chao, L.-W., Szrek, H., Pereira, N.S., Pauly, M.V., 2009. Time preference and its relationship with age, health, and survival probability. Judgm. Decis. Mak. 4, 19.
Cohen, J., Ericson, K.M., Laibson, D., White, J.M., 2020. Measuring time preferences. J. Econ. Lit. 58, 299–347. https://doi.org/10.1257/jel.20191074.
Croson, R., Gneezy, U., 2009. Gender differences in preferences. J. Econ. Lit. 47, 448–474. https://doi.org/10.1257/jel.47.2.448.
Dittrich, M., Leipold, K., 2014. Gender differences in time preferences. Econ. Lett. 122, 413–415. https://doi.org/10.1016/j.econlet.2014.01.002.
Ersner-Hershfield, H., Garton, M.T., Ballard, K., Samanez-Larkin, G.R., Knutson, B., 2009. Don't stop thinking about tomorrow: Individual differences in future self-continuity account for saving. Judgm. Decis. Mak. 4, 280–286.
Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., Sunde, U., 2018. Global evidence on economic preferences. Q. J. Econ. 133, 1645–1692. https://doi.org/10.1093/qje/qjy013.
Fisher, I., 1930. The Theory of Interest: As Determined by Impatience to Spend Income and Opportunity to Invest It. Macmillan, New York.
Frederick, S., Loewenstein, G., O'Donoghue, T., 2002. Time discounting and time preference: a critical review. J. Econ. Lit. 40, 351–401. https://doi.org/10.1257/002205102320161311.
Green, L., Fry, A.F., work(s), J.M.R., 1994. Discounting of delayed rewards: a life-span comparison. Psychol. Sci. 5, 33–36.
Grossman, M., 2006. Education and nonmarket outcomes. in Handbook of the Economics of Education. Elsevier, pp. 577–633. https://doi.org/10.1016/S1574-0692(06)01010-5.
Harrison, G.W., Lau, M.I., Williams, M.B., 2002. Estimating individual discount rates in denmark: a field experiment. Am. Econ. Rev. 92, 1606–1617. https://doi.org/10.1257/000282802762024674.
Haushofer, J., Schunk, D., Fehr, E., 2013. Negative income shocks increase discount rates. Unpublished manuscript 769–92.
Huffman, D., Maurer, R., Mitchell, O.S., 2019. Time discounting and economic decision-making in the older population. J. Econ. Ageing 14, 100121. https://doi.org/10.1016/j.jeoa.2017.05.001.
Hunter, R.F., Tang, J., Hutchinson, G., Chilton, S., Holmes, D., Kee, F., 2018. Association between time preference, present-bias and physical activity: implications for designing behavior change interventions. BMC Public Health 18, 1388. https://doi.org/10.1186/s12889-018-6305-9.
Kang, M.I., Ikeda, S., 2014. Time discounting and smoking behavior: evidence from a panel survey. Health Econ. 23, 1443–1464. https://doi.org/10.1002/hec.2998.
Koopmans, T.C., 1960. Stationary ordinal utility and impatience. Econometrica 28, 287. https://doi.org/10.2307/1907722.
Lawrance, E.C., 1991. Poverty and the rate of time preference: evidence from panel data. J. Polit. Econ. 99, 54–77. https://doi.org/10.1086/261740.
Meier, S., Sprenger, C., 2010. Present-biased preferences and credit card borrowing. Am. Econ. J. Appl. Econ. 2, 193–210. https://doi.org/10.1257/app.2.1.193.
Musau, A., 2009. Modeling alternatives to exponential discounting. MPRA Paper No. 16416 70.
O'Donoghue, T., Rabin, M., 2015. Present bias: lessons learned and to be learned. Am. Econ. Rev. 105, 273–279. https://doi.org/10.1257/aer.p20151085.
O'Donoghue, T., Rabin, M., 1999. Doing it now or later. Am. Econ. Rev. 89, 103–124.
OECD, 2015. Pensions at a Glance 2015: OECD and G20 indicators, OECD Pensions at a Glance. OECD. https://doi.org/10.1787/pension_glance-2015-en.
Ogaki, M., Atkeson, A., 1997. Rate of time preference, intertemporal elasticity of substitution, and level of wealth. Rev. Econ. Stat. 79, 564–572. https://doi.org/10.1162/003465397557141.
Paula, J.J.D., Paiva, G.C.D.C., Costa, D.D.S., 2015. Use of a modified version of the switching verbal fluency test for the assessment of cognitive flexibility. Dement. Neuropsychol. 9, 258–264. https://doi.org/10.1590/1980-57642015dn93000008.
Prelec, D., Loewenstein, G., 1998. The red and the black: mental accounting of savings and debt. Mark. Sci. 17, 4–28.
Prince, J.T., Shawhan, D.L., 2011. Is time inconsistency primarily a male problem? Appl. Econ. Lett. 18, 501–504. https://doi.org/10.1080/13504851003761806.
Richter, D., Mata, R., 2018. Age differences in intertemporal choice: U-shaped associations in a probability sample of German households. Psychol. Aging 33, 782–788. https://doi.org/10.1037/pag0000266.
Rieger, M.O., Wang, M., Hens, T., 2021. Universal time preference. PLoS One 16, e0245692. https://doi.org/10.1371/journal.pone.0245692.
Rogers, A.R., 1994. Evolution of time preference by natural selection. Am. Econ. Rev. 84, 460–481.
Ross, C.E., Mirowsky, J., 1999. Refining the association between education and health: the effects of quantity, credential, and selectivity. Demography 36, 445–460.
Samuelson, P.A., 1937. A note on measurement of utility. Rev. Econ. Stud. 4, 155. https://doi.org/10.2307/2967612.
Schneeweis, N., Skirbekk, V., Winter-Ebmer, R., 2014. Does education improve cognitive performance four decades after school completion? Demography 51, 619–643. https://doi.org/10.1007/s13524-014-0281-1.
SHARE, 2020. SHARE release guide 7.1.0.
Sozou, P.D., Seymour, R.M., 2003. Augmented discounting: interaction between ageing and time–preference behaviour. In: Proceedings of the Royal Society of London Series B: Biological Sciences, 270, pp. 1047–1053. https://doi.org/10.1098/rspb.2003.2344.
Sutter, M., Kocher, M.G., Glätzle-Rützler, D., Trautmann, S.T., 2013. Impatience and uncertainty: experimental decisions predict adolescents' field behavior. Am. Econ. Rev. 103, 510–531. https://doi.org/10.1257/aer.103.1.510.
Tanaka, T., Camerer, C.F., Nguyen, Q., 2010. Risk and time preferences: linking experimental and household survey data from Vietnam. Am. Econ. Rev. 100, 557–571. https://doi.org/10.1257/aer.100.1.557.
Thaler, R.H., 1999. Mental accounting matters. J. Behav. Decis. Mak. 12, 183–206. https://doi.org/10.1002/(SICI)1099-0771(199909)12:3<183::AID-BDM318>3.0.CO;2-F.
Trostel, P.A., Taylor, G.A., 2001. A theory of time preference. Econ. Inq. 39, 379–395. https://doi.org/10.1093/ei/39.3.379.
Wang, M., Rieger, M.O., Hens, T., 2016. How time preferences differ: evidence from 53 countries. J. Econ. Psychol. 52, 115–135. https://doi.org/10.1016/j.joep.2015.12.001.
Whelan, R., McHugh, L.A., 2009. Temporal discounting of hypothetical monetary rewards by adolescents, adults, and older adults. Psychol. Rec. 59, 247–258. https://doi.org/10.1007/BF03395661.