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Temporal Discounting in Later Life

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Temporal Discounting in Later Life

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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.

JEL Classification: D12, D15, C83, J14

Keywords: Time preferences, Discount rate, Present bias, Survey methodology, Old age

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I. 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 small survey 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 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)). The identified heterogeneity of preferences suggests lower degree of patience among rural dwellers, and greater patience of individuals with higher incomes and numerical cognition.

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.

II. 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 behaviour. 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, 1999, 2015) – 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), also time preferences may 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 labour market opportunities to further their education (Grossman, 2006) while on the other, 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.

III. 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 behaviour (Frederick *et al.* 2002). Further legitimized by Koopmans' (1960) behavioural 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:

$$D(y,t) = e^{-rt} \qquad \text{Where } r > 0 \text{ and } t > 0 \qquad [1]$$

$$D(y,t) = \frac{1}{1+rt} \qquad \text{Where } r > 0 \text{ and } t > 0 \qquad [2]$$

$$D(y,t) = \beta e^{-rt} \qquad \text{Where } r > 0, \quad 0 < \beta < 1 \text{ and } t > 0 \qquad [3]$$

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 Equation [3] takes a variable cost. As highlighted by Benhabib *et al.* (2010), the amount $\$y$, when received in the future, is valued as $\$y - (1-\beta)y$, 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 Equation [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].

$$D(y,t) = e^{-rt}(y + be^{-mt}) - b = \begin{cases} D(y,t) = e^{-rt} - (1 - e^{-rt})\,\frac{b}{y} & \text{if m = 0} \qquad [4] \\ D(y,t) = e^{-rt} - \frac{b}{y} & \text{if m} = \infty \qquad [5] \end{cases}$$

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

IV. 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 Tanaka *et al.* (2010). The drop-off presented respondents with 40 hypothetical choice tasks to elicit their time preferences. In the survey, the 1,826 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, 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 1,826 Polish respondents of the main CAPI interview the survey yielded 1,601 drop-off responses, of which 1,418 were fully completed. These responses have been 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, 62 were completed inconsistently judging by preference transitivity ($z > y \ if \ \ x > y$ and $\forall z > x$).[2]

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, we cannot identify preferences for the *always patient* and the *always impatient* respondents, as their choices only

[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).

[2] In the set-up of the module transitivity requires that when a respondent prefers an immediate amount (*x)* to a delayed amount (*y),* at a delay (t>0), then they ought to prefer any larger immediate amount (*z>x)* with an identical delay, over the same future payment.

narrow down either the lower or the upper bound of their discount rate. Consequently, only mixed (and consistent) responses could be used, and thus our final estimation of time preferences is conducted using the sample of 725 respondents (Table 1).

Table 1: Completion of the SHARE drop-off questionnaire

	No. of respondents
Total sample:	1,826
Main survey only (no drop-off)	225
Incomplete drop-offs	183
Completed drop-offs	1,418
Distribution of completed drop-offs:	
a. Always patient	526
b. Mixed and consistent	725
c. Mixed and inconsistent	62
d. Always impatient	105

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

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, 2019a, 2019c, 2019b, 2019d, 2020). 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).

Table 2: Complete responses summary statistics

	Surveys	Mean	Std. Dev.	Minimum	Maximum
Age	1,418	66.419	9.493	41	96
Female	1,418	0.566	0.496	0	1
Years of education	1,418	10.185	3.256	0	23
Number of children	1,418	2.480	1.453	0	13
ln(Income)	1,418	8.728	0.767	4.171	11.884
Verbal fluency (standardized)	1,418	0.000	1	-2.708	12.138
Numerically cognizant	1,418	0.713	0.453	0	1
Marital Status	1,418				
Married, living together	1,028	0.725			
Married, living separately	22	0.016			
Never married	46	0.032			
Divorced	56	0.039			
Widowed	266	0.188			
Labour market status	1,418				
Retired	869	0.613			
Employed/self-employed	289	0.204			
Unemployed	49	0.035			
Permanently sick/disabled	92	0.065			
Homemaker	36	0.025			
Other	83	0.059			
Health	1,418				
Excellent	19	0.013			
Very good	102	0.072			
Good	547	0.386			
Fair	470	0.331			
Poor	280	0.197			
Location	1,418				
Big city	209	0.147			
Suburbs/Outskirts of big city	35	0.025			
Large town	328	0.231			
Small town	155	0.109			
Rural area/Village	691	0.487			

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.

Although majority of the respondents were in their 60s, 13 participants in the sample were aged below 50 years of age, and 298 respondents were aged 75 or over. The sample is also characterized by relatively greater proportions of women (56.6%), married and cohabiting respondents (72.5%), retirees (61.3%), and rural dwellers (48.7%). The statistics also highlight that a non-negligible portion of the sample resides in urban areas—a big city or a large or small town. The Polish SHARE sample is also characterised by low numbers of individuals with excellent self-rated health (1.3%) as well as those that are married but living separately from their spouse (1.6%).

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. 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.

Table 3: Correlates of broad response categories

	Always patient	Std. Err.	Always impatient	Std. Err.
Age	0.002	0.004	0.001	0.001
Female	0.014	0.025	0.002	0.016
Years of education	-0.017***	0.006	-0.004	0.003
Number of children	0.011	0.010	-0.011	0.008
ln(Income)	0.068***	0.025	-0.032***	0.009
Verbal fluency (standardized)	0.001	0.025	-0.001	0.012
Numerically cognizant	0.072	0.044	-0.003	0.021
Marital status				
Married, living separately	0.211	0.142	-0.036	0.046
Never married	-0.081	0.073	-0.013	0.035
Divorced	0.058	0.065	-0.012	0.032
Widowed	0.095*	0.049	-0.034**	0.015
Labour market status				
Employed/self-employed	0.051	0.067	-0.014	0.022
Unemployed	-0.059	0.070	-0.033	0.027
Permanently sick/disabled	-0.022	0.063	0.010	0.024
Homemaker	-0.201**	0.078	-0.027	0.039
Other	-0.043	0.063	-0.004	0.033
Location				
Rural area/Village	-0.014	0.045	-0.021	0.020
Health				
Poor Health	0.019	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: 1418 — 'Always patient' category: 526 observations, 'Always impatient' category: 105 observations; 'Mixed reply' category (787 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, living together,* Labour market status: *Retired,* Location: *Big city,* Health: all individuals whose self-perceived health is *excellent, very good, good* or *fair.*

Few of the examined characteristics are significantly correlated with the probability of being in either of the *always patient* or *always impatient* categories. An additional year of education reduces the average probability of always being patient by -0.017 percentage points. The results also show that, relative to retirees, homemakers are -0.201 percentage points less likely to always be patient. Higher income increases the average probability of being always patient and consistently reduces that of being always impatient. Relative to both being in the 'Mixed reply' category and to cohabiting married individuals, widowed respondents are more likely to be '*always patient*' and less likely to be '*always impatient*'.

Table 4: Probability estimates of response consistency

	Coefficient	**Std. Err.**
Constant	0.638	0.450
Age	0.009	0.012
Age^2	0.000	0.000
Female	-0.014	0.013
Years of education	-0.001	0.001
Number of children	0.002	0.003
ln(Income)	-0.005	0.008
Verbal fluency (standardized)	-0.001	0.007
Numerically cognizant	-0.004	0.019
Marital status		
Married, living separately	0.002	0.045
Never married	0.015	0.031
Divorced	0.051***	0.013
Widowed	0.011	0.016
Labour market status		
Employed/self-employed	0.055*	0.031
Unemployed	-0.039	0.053
Permanently sick/disabled	0.005	0.021
Homemaker	0.013	0.036
Other	-0.031	0.033
Location		
Rural area/Village	-0.007	0.013
Health		
Poor Health	-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. 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.

Since the sample for our final estimation excludes the 62 individuals who gave 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. The only exception is being divorced, while working or being self-employed is only marginally significant.

Ultimately, to measure the time discounting of the survey respondents, we limit our analysis to the 725 respondents who gave complete, mixed and consistent responses. As we saw above there is little regularity with respect to inconsistency of answers given in the survey (Table 4). However, given the patterns identified from the point of view of declared patience we need to bear in mind the potential bias resulting from the uncovered patterns in the sample classification, in particular with regard to income and marital status (Table 3). In the latter case an important lesson from the conducted exercise for any future application of similar question modules in surveys, is to cover a broad range of monetary response categories to ensure a high proportion of *mixed replies*.

V. 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 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 β = 1, b = 0 and θ approaches its limit (=1)*;* hyperbolic discounting when β = 1, b = 0 and θ = 2; traditional quasi-hyperbolic (βe^{-rt}), wherein the present bias cost is variable, when *θ = 1, b = 0* and *β* is unconstrained; and a quasi-hyperbolic specification with a fixed present bias cost $(e^{-rt}-b)$ when only θ = 1 and β = 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 β < 1, and with a fixed cost whenever b > 0.

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

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

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. 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.

Table 5: Estimates of discounting models

	Exponential	**Hyperbolic**	**Quasi-Hyperbolic**	**Quasi-Hyperbolic (UFC)**	**Quasi-Hyperbolic (DFC)**
μ	0.006***	0.006***	0.008***	0.007***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r	0.005***	0.007***	0.003***	0.004***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β			0.872***		
			(0.007)		
b				38.147***	-71.645**
				(6.036)	(28.529)
Observations	29,000	29,000	29,000	29,000	29,000
Respondents	725	725	725	725	725
Log-likelihood	-15407.97	-15340.89	-14975.21	-15361.56	-15403.32
Adjusted-R^2	0.424	0.427	0.441	0.426	0.424
AIC	30819.94	30685.78	29956.42	30729.12	30812.63
BIC	30836.49	30702.34	29981.24	30753.95	30837.46

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.

The present bias (β=0.872) 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) 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. 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 Equation [7] and its results are provided in Table 6.

$$P(x > (y,t) = \frac{1}{1 + \exp[-\mu(x - y\beta\exp(-rt))]}\ , \quad \text{where } r = \sum_{0}^{n} r_i X \ \text{ and } \ \beta = \sum_{0}^{n} \beta_i X \qquad [7]$$

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), we find that the included socioeconomic variables explain some of the heterogeneity of individual present bias (β). For instance, being widowed, a homemaker, and the income available to the household, are statistically significant correlates of present bias. Specifically, widowed respondents and homemakers exhibit lower patience via the present bias, relative to married and cohabiting respondents and retirees, respectively. Years of schooling and income also constitutes another positive correlate of patience through present bias.

Importantly, those with greater numerical competency display greater patience through a higher discount rate (*r*). In contrast to the present bias estimates, being either a widow or homemaker is also negatively correlated with (*r*) reflecting higher patience via the discount rate. The discount rate estimates also suggest that permanently sick or disabled individuals are more patient than retirees. Finally, the residence location of the respondents is revealed to be associated to their temporal preferences, with rural dwellers relatively less likely to defer gratification.

Table 6: Time preference heterogeneity estimates

	β	**Robust Std. Err.**	***r***	**Robust Std. Err.**
μ	0.008***	0.000		
Constant	0.912**	0.443	1.131*	0.644
Age	-0.005	0.012	-0.016	0.018
Age^2	0.000	0.000	0.000	0.000
Female	-0.009	0.018	-0.010	0.027
Years of education	-0.006*	0.003	0.004	0.006
Number of children	0.002	0.006	-0.011	0.011
ln(Income)	0.025**	0.012	-0.022	0.018
Verbal fluency (standardized)	0.008	0.010	0.002	0.012
Numerically cognizant	-0.030	0.020	-0.082***	0.030
Marital status				
Married, living separately	0.076	0.095	-0.084	0.106
Never married	0.050	0.045	0.018	0.074
Divorced	0.034	0.041	0.002	0.066
Widowed	-0.053**	0.027	-0.069*	0.040
Labour market status				
Employed/self-employed	0.041	0.028	-0.059	0.041
Unemployed	0.031	0.044	0.068	0.082
Permanently sick/disabled	-0.043	0.037	-0.137**	0.054
Homemaker	-0.171***	0.054	-0.251***	0.059
Other	-0.009	0.036	0.136	0.061
Location				
Rural area/Village	0.019	0.018	0.046*	0.027
Health				
Poor Health	-0.020	0.022	0.027	0.038
Observations	29000			
Respondents	725			
Adjusted-R^2	0.450			
Log-Likelihood	-14746.2			
AIC	29574.39			
BIC	29913.67			

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); 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.

Because widowhood and being a homemaker are negatively correlated with both the present bias and the discount rate, the overall effect of these characteristics on patience is ambiguous. To identify the overall effects we thus further probe their absolute correlation with patience using expected values simulated conditional on the assumed binary states in each of the cases. The mean expected probabilities are provided in Appendix D and suggest that widowed respondents are marginally more patient than married respondents, while the expected probabilities of choosing the delayed option for homemakers suggest that they are more patient compared to retirees.

VI. 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 more often with the present-bias parameter than with the discount rates. The results highlight significant relationships between the time preference parameters and numerical abilities, household income and whether the respondent is widowed or a homemaker. 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.

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 find a number of statistically significant relations of discounting with socio-demographic characteristics. This 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.

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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 ($k.1 - k.5$, $where\ \ k = 6, \dots, 13$) 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: Category distributions of surveys

	Complete Responses	Consistent responses	Always Patient	Mixed Responses	Always impatient
Age	1418	1356	526	787	105
Female	1418	1356	526	787	105
Years of Education	1418	1356	526	787	105
Number of children	1418	1356	526	787	105
ln(Income)	1418	1356	526	787	105
Verbal fluency	1418	1356	526	787	105
Numeracy	1418	1356	526	787	105
0 subtractions	66	65	32	30	4
1 subtraction	93	90	34	45	14
2 subtractions	73	72	30	38	5
3 subtractions	158	148	40	106	12
4 subtractions	238	227	80	142	16
5 subtractions	773	737	303	416	54
Refusal	17	17	7	10	
Marital Status	1418	1356	526	787	105
Married, living together	1028	978	367	586	75
Married, living separately	22	21	12	9	1
Never married	46	44	9	32	5
Divorced	56	56	20	31	5
Widowed	266	257	118	129	19
Labour market status	1418	1356	526	787	105
Retired	869	833	345	453	71
Employed/self-employed	289	282	108	166	15
Unemployed	49	44	11	35	3
Permanently sick/disabled	92	87	29	55	8
Homemaker	36	34	6	28	2
Other	83	76	27	50	6
Health	1418	1356	526	787	105
Excellent	19	19	7	10	2
Very good	102	99	46	49	7
Good	547	517	169	336	42
Fair	470	452	191	249	30
Poor	280	269	113	143	24
Location	1418	1356	526	787	105
Big city	209	199	77	113	19
Suburbs/Outskirts of big city	35	33	7	23	5
Large town	328	314	123	179	26
Small town	155	150	59	88	8
Rural area/Village	691	660	260	384	47

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

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 1051 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)).responses are also provided in Table B. The The different categories of the categorical variables — marital status, labour market status, health, and location —, and their distributions under the different groupings of marital status variable is used to generate the dummy variables: *separated* (=1 if married and living separately), *nmarried* (=1 if respondent was never married), *divorced* (=1) and *widowed* (=1). *Semployed* (=1 if respondent is self-employed or employed), *unemployed* (=1), *disabled* (=1 if permanently disabled or sick), *homemaker* (=1) and *otlstat* (=1 if the respondent's labour market status is other) are dummies generated from the labour market status. Finally, out of the location and health variables we generate the poor self-perceived health (*phealth=1*) and rural dwelling (*rural=1*) 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.

Table C: Multinomial logistic regression of complete responses

	Always patient	**Robust Std. Err.**	**Always impatient**	**Robust Std. Err.**
Constant	-2.267	4.443	-1.717	5.182
Age	-0.006	0.125	0.118	0.141
Age^2	0.000	0.001	-0.001	0.001
Female	0.071	0.108	0.054	0.237
Years of education	-0.087***	0.031	-0.098**	0.043
Number of children	0.029	0.045	-0.154	0.119
ln(Income)	0.259**	0.115	-0.380**	0.150
Verbal fluency (standardized)	0.002	0.109	-0.007	0.170
Numerically cognizant	0.334*	0.196	0.088	0.310
Marital status				
Married, living separately	0.875	0.622	-0.180	1.081
Never married	-0.432	0.391	-0.330	0.542
Divorced	0.247	0.285	-0.075	0.500
Widowed	0.365*	0.213	-0.410	0.260
Labour market status				
Employed/self-employed	0.207	0.293	-0.135	0.372
Unemployed	-0.337	0.342	-0.704	0.622
Permanently sick/disabled	-0.084	0.293	0.106	0.315
Homemaker	-1.161**	0.569	-0.786	0.853
Other	-0.214	0.296	-0.140	0.494
Location				
Rural area/Village	-0.105	0.195	-0.360	0.270
Health				
Poor Health	0.098	0.158	0.100	0.284
Respondents	1418			
Log-pseudo-likelihood	-1214.379			
Chi^2 p-value	0.000			
Pseudo R^2	0.035			

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

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, living together,* 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: Expected probabilities to calculate the implications of selected characteristics for patience

Widowed and homemaker estimates from the disaggregation of both the present bias and discount rate offer conflicting correlations. Both are associated negatively to patience via the present bias and negatively via the discount rate, with respect to their respective reference groups. We therefore simulate the marital status of all respondents as widowed and married and cohabiting separately, and obtain their separate expected probabilities of choosing a delayed reward (y) in t days over an immediate one (x). Thereafter, we iterate the above procedure with homemaker and retiree in place of widowed and married and cohabiting. A summary of the expected probabilities are provided in Table E.

Table D: Expected probabilities of choosing a delayed option

Simulated variable	**Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**
Marital Status					
Widowed	29,000	0.309	0.259	0.000	0.993
Married	29,000	0.282	0.249	0.000	0.992
Labour Market Status					
Homemaker	29,000	0.378	0.282	0.000	0.991
Retired	29,000	0.287	0.251	0.000	0.989

Source: Own calculations based on the Polish sample of SHARE wave 6 using model estimates from Table 6.