Time Discounting and Wealth Inequality

Thomas Epper, Ernst Fehr, Helga Fehr-Duda, Claus Thustrup Kreiner, David Dreyer Lassen, Søren Leth-Petersen, and Gregers Nytoft Rasmussen

Online Appendix

A Theory

A.1 Derivation of equation (3)

The solution to the maximization problem is characterized by the standard Euler equation/Keynes-Ramsey rule

$$\frac{\dot{c}(a)}{c(a)} = \frac{r-\rho}{\theta} \tag{5}$$

and the transversality condition $w(T) = 0$. By integrating the flow budget constraint (2), we obtain the following intertemporal budget constraint

$$w(a) = e^{ra}\left[w(0) + \int_0^a y(\tau)e^{-r\tau}d\tau - \int_0^a c(\tau)e^{-r\tau}d\tau\right]. \tag{6}$$

By evaluating (6) at $a = T$ and using $w(T) = 0$ in the optimum, we obtain

$$Y \equiv w(0) + \int_0^T y(\tau)e^{-r\tau}d\tau = \int_0^T c(\tau)e^{-r\tau}d\tau.$$

By integrating (5), we obtain

$$c(a) = c(0)e^{\frac{r-\rho}{\theta}a}, \tag{7}$$

which is substituted into the above equation in order to get

$$Y(0) = c(0) \int_0^T e^{\frac{r(1-\theta)-\rho}{\theta}\tau} d\tau.$$

By solving the integral and isolating $c(0)$, we obtain

$$c(0) = Y(0) \frac{\rho + r(\theta - 1)}{\theta \left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right)}. \tag{8}$$

Next, we substitute equation (7) into (6), which gives

$$w(a) = e^{ra} \left[w(0) + \int_0^a y(\tau) e^{-r\tau} d\tau - c(0) \frac{\theta}{r(1-\theta) - \rho} \left(e^{\frac{r(1-\theta)-\rho}{\theta} a} - 1 \right) \right],$$

and we use expression (8) to substitute for $c(0)$, which gives

$$w(a) = e^{ra} \left[w(0) + \int_0^a y(\tau) e^{-r\tau} d\tau - Y \frac{1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}}{1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}} \right].$$

Finally, this equation is rewritten to (3) by using the definition of $\gamma(a)$.

A.2 Relationship between patience and wealth

Differentiating equation (3) with respect to ρ gives:

$$\frac{\partial w(a)}{\partial \rho} = -Y \frac{\frac{a}{\theta} e^{\frac{r(1-\theta)-\rho}{\theta} a} \left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right) - \frac{T}{\theta} e^{\frac{r(1-\theta)-\rho}{\theta} T} \left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}\right)}{\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right)^2} e^{ra}. \tag{9}$$

Higher patience (lower ρ) leads to higher wealth, $\frac{\partial w(a)}{\partial \rho} \leq 0$, iff

$$\begin{aligned} a e^{\frac{r(1-\theta)-\rho}{\theta} a} \left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right) - T e^{\frac{r(1-\theta)-\rho}{\theta} T} \left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}\right) &\geq 0 \quad \Leftrightarrow \\ \frac{e^{kT} - 1}{T} - \frac{e^{ka} - 1}{a} &\geq 0, \end{aligned}$$

where $k \equiv \frac{\rho - r(1-\theta)}{\theta}$. The function $\frac{e^{ka}-1}{a}$ equals k when $a \to 0$ (which may be seen by applying l'Hôpital's rule) and is increasing in a for all values of $k \neq 0$. For $T > a$, this implies that $\frac{e^{kT}-1}{T} > \frac{e^{ka}-1}{a}$. Hence, the above inequality is always fulfilled.

B Experiment

B.1 Invitation letter

Below is a copy of the invitation letter (in Danish) and an English translation.

Figure A1: Invitation letter

ØKONOMISK INSTITUT
KØBENHAVNS UNIVERSITET

[redacted]

FEBRUAR 2015

ØKONOMISK INSTITUT

ØSTER FARIMAGSGADE 5,
BYGNING 26
1353 KØBENHAVN K

TLF 35 33 02 77

analyse@econ.ku.dk

Dataansvarlig: Søren Leth-Petersen,
Professor

Kære [redacted],

Københavns Universitet inviterer dig til at deltage i en undersøgelse på internettet. Undersøgelsen er en del af et forskningsprojekt, der handler om at forstå grundlaget for danskernes økonomiske beslutninger. Vi ved allerede meget mere om folks privatøkonomiske beslutninger, end vi gjorde før den finansielle krise, men der er stadig meget, vi mangler at forstå – og det er derfor, vi spørger om din hjælp.

Det tager ca. 30-50 minutter at gennemføre undersøgelsen. Når du er færdig, vil du typisk modtage et præmiebeløb, og det vil automatisk blive overført til din NemKonto. Beløbets størrelse afhænger bl.a. af de valg, som du træffer i undersøgelsen og vil i gennemsnit svare til en god timeløn.

Undersøgelsen foregår på internettet. Du vil bl.a. blive bedt om at tage stilling til spørgsmål om opsparing og investering. Reglerne bliver forklaret, når du har logget ind. Undersøgelsen er åben for deltagelse til og med fredag d. 27. februar 2015.

Datatilsynet har godkendt forskningsprojektet, hvilket betyder, at vores procedurer opfylder persondatalovens krav til behandling af data. En vigtig del af Datatilsynets krav er, at dine svar bliver behandlet anonymt. For at sikre dig anonymitet har vi dannet et tilfældigt brugernavn til dig. For at deltage skal du logge ind på hjemmesiden: **analyse.econ.ku.dk.**

Brugernavn: deltager5795 Password: n4mw9!uay

Invitationen er personlig, og vi beder derfor om, at du ikke videregiver brugernavn og password til andre. Du er velkommen til at kontakte os, hvis du har problemer med at logge ind eller har yderligere spørgsmål. Du kan ringe til projektkoordinator Gregers Nytoft Rasmussen på telefonnummer 35 33 02 77 mandag-torsdag kl. 14.00-17.30 eller skrive til adressen analyse@econ.ku.dk.

Med venlig hilsen

Søren Leth-Petersen
Søren Leth-Petersen
Projektleder, professor

English translation of the invitation letter:

Dear «name»,

University of Copenhagen invites you to participate in a study on the Internet. The study is part of a research project about understanding the basis for the Danes' financial decisions. We already know a lot more about people's personal financial decisions than we did before the financial crisis, but there is still much we need to understand - and that is why we are asking for your help.

It takes about 30-50 minutes to complete the study. When you are finished, you will typically receive prize money, and it will be automatically transferred to your NemKonto. The amount depends, i.a., on the choices that you make during the study and will on average correspond to a decent hourly wage.

The study is conducted on the Internet. You will consider questions concerning savings and investments, among other things. The rules will be explained once you have logged in. The study is open for participation through «date».

The Data Protection Agency has approved the research project, which means that our procedures comply with the Act on Processing of Personal Data. An important part of the Data Protection Agency's requirements is that your answers will be treated anonymously. To ensure anonymity, we have formed a random username for you. To participate, please log in at the following website: **analyse.econ.ku.dk**.

Username: «username» Password: «password»

The invitation is personal and we therefore ask you not to pass on your username and password to others. Please feel free to contact us if you are having trouble logging in or have any further questions. You can call project coordinator Gregers Nytoft Rasmussen at phone number 35 33 02 77 Monday-Thursday 2:00 p.m. – 5:30 p.m. or write to the address analyse@econ.ku.dk.

Sincerely yours,

Søren Leth-Petersen

Project manager, professor

B.2 Choice situations for time task

Table A1 presents a list of all choice situations in the time task. x_1 is the value of a block allocated at t_1. x_2 is the value of a block allocated at t_2. t_1 and t_2 are delays in weeks. 'delay' corresponds to the difference between t_2 and t_1. 'annual rate' is the annual rate of return imputed by the relative values of the blocks. It is defined as $\frac{1}{(t_1-t_2)/52}\ln\left(\frac{x_1}{x_2}\right)$. 'slope' denotes the slope of the budget line in (x_1, x_2)-space, i.e. $-\frac{x_2}{x_1}$.

Table A1: Intertemporal choice situations

choiceId	x_1	x_2	t_1	t_2	delay	annual rate (%)	slope
1	100	105	0	8	8	31.7	-1.050
2	100	110	0	8	8	62.0	-1.100
3	100	115	0	8	8	90.8	-1.150
4	100	120	0	8	8	118.5	-1.200
5	100	125	0	8	8	145.0	-1.250
6	100	105	0	16	16	15.9	-1.050
7	100	115	0	16	16	45.4	-1.150
8	100	125	0	16	16	72.5	-1.250
9	100	135	0	16	16	97.5	-1.350
10	100	145	0	16	16	120.8	-1.450
11	100	105	8	16	8	31.7	-1.050
12	100	110	8	16	8	62.0	-1.100
13	100	115	8	16	8	90.8	-1.150
14	100	120	8	16	8	118.5	-1.200
15	100	125	8	16	8	145.0	-1.250

B.3 Comparing the experimental results to previous work

In this appendix, we compare our choice data from the time discounting experiment to similar choice data from a related study (Andreoni and Sprenger 2012 [AS]), and we show that estimated discount rates, using four different specifications of a random utility model, are within the range found by other studies.

Comparing to Andreoni and Sprenger (2012): Although there are some differences between the budget choice designs and the selected populations in our study and AS, we show that the overall behavior found in the two data sets appears to be both qualitatively and quantitatively similar. Our patience measure is constructed using five choice situations. In each of these five choice situations, subjects chose to allocate 10 blocks between an earlier point in time (8 weeks, i.e. 56 days in the future) and a later point in time (16 weeks, i.e. 112 days in the future). Subjects in the AS study faced a series of related budget choices. They were asked to allocate 100 tokens between two different payment dates in each of these budget choices. For comparability, we pick the most similar delays in their experiment, namely 35 and 70 days. In addition to different delays and different numbers of blocks/tokens to allocate, the two studies vary with respect to the subject sample and the presentation format. Specifically, the AS sample consists of 97 San Diego undergraduates, whereas our study uses data from 3,620 middle-aged individuals from the general Danish population. In their experiment, subjects were presented an ordered list of allocation choices with fixed payment dates on each screen. In contrast, we displayed each allocation choice in our study separately on a new screen. The five allocation choices we use to construct our patience index were interleaved with other choices involving different payment dates, and they appeared in randomized order. Furthermore, we held the value of an earlier block fixed at 100 points, whereas AS fixed the price of a future token for each date configuration.

Figure A2 juxtaposes the average share of blocks/tokens that subjects postponed to the later date as a function of the relative gain measured in percent from delaying it. In both experiments, it is as expected that the higher the compensation ('gain of postponing'), the more the subjects are willing to postpone gratification. Importantly, the average behavior found in the the two data sets appears to be both qualitatively and quantitatively very similar.

Estimating discount rates: Here, we describe the results of structural estimation of individual discount rates. Consider the decision problem from the subject's perspective. Define a choice situation S (see rows in Table A1) as a tuple of attributes (x_1, t_1, x_2, t_2), where x_1 and x_2 denote the value (points) of a block materializing at the earlier point in time t_1 and the later point in time t_2, respectively. Delays will be reported in calendar weeks.

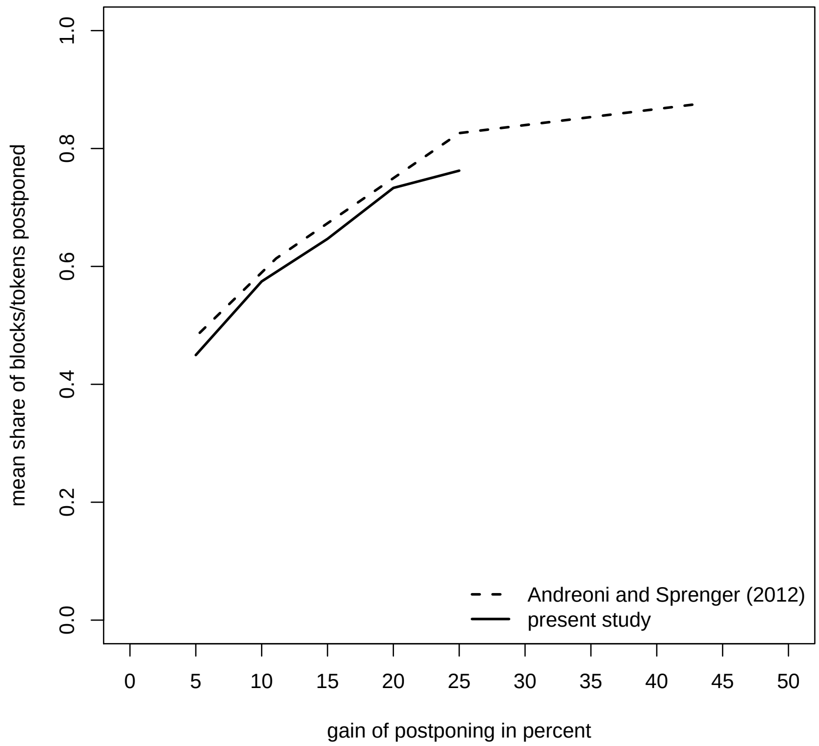
Assuming additively separable time discounting, a subject's choice z is the outcome of the maximization problem

$$\max_{z \in \{0,1,\ldots,10\}} d(t_1)u(w_1) + d(t_2)u(w_2)\,,$$

subject to the budget constraint

$$w_2 = -\frac{x_2}{x_1}(w_1 - 10x_1)\,,$$

Figure A2: Comparing choices in our experiment to existing work



Notes: The figure shows the average share of blocks/tokens postponed to the later date by the subjects as a function of the relative gain measured in percent from delaying it. For our data, the gain is calculated as the value of a later block in points measured in percent of the point value of a sooner block. For Andreoni and Sprenger (2012), the gain is calculated as the price of a later token in percent of the price of a sooner token.

where $w_1 = (10 - z)x_1$ and $w_2 = z \cdot x_2$ denote the total number of points allocated to t_1 and t_2, respectively. Therefore, $z \in \{0, 1, ..., 10\}$ indicates the number of blocks saved to the later point in time. In our setup, it holds that $x_1 = 100$ points in every choice situation. The slope of the budget lines is thus given by $-\frac{x_2}{100}$.

In order to make the model operational, we have to assume specific functional forms for the discount function $d(t)$ and the utility function $u(w)$. We start with introducing our most general specification and then discuss variants of the model imposing restrictions on certain behavioral parameters. For the discount function $d(t)$, we use the quasi-hyperbolic form (Laibson 1997)

$$d(t) = \begin{cases} 1 & \text{if } t = 0 \\ \beta e^{-\rho \frac{t}{52}} & \text{if } t > 0 \end{cases},$$

where ρ denotes the annualized discount rate and $\beta < 1$ denotes present bias. The utility function $u(w)$ takes the iso-elastic form

$$u(w) = \begin{cases} w^{1-\theta} & \text{if } \theta < 1 \\ \ln(w) & \text{if } \theta = 1 \\ -w^{1-\theta} & \text{if } \theta > 1 \end{cases},$$

where θ denotes an Arrow-Pratt-type coefficient of relative aversion towards income fluctuations. We normalize such that $u(\min(w_2)) = 0$ and $u(\max(w_1)) = 1$. Note that a single choice situation S only informs us about whether an individual is more or less patient than a certain threshold (see the rates listed in Table A1). The fact that we observe multiple choices per subject and that these choice situations vary with respect to their implicit interest rates permit us to bound the discount rate to an interval.

We estimate four different models:

- **Model 1:** To be able to compare estimated discount rates with our non-parametric index of patience, we first restrict attention to choice situations with payment dates $t_1 = 8$ weeks and $t_2 = 16$ weeks. Based on the five choice situations satisfying this requirement, we estimate the discount rate ρ. As these situations involve tradeoffs between two future dates only, they do not permit identification of the present bias parameter β. Furthermore, for this specification we also restrict utility to be linear in outcomes, such that $\theta = 0$.

- **Model 2:** This model's specification is equivalent to the specification of Model 1, but we estimate it on all 15 choice situations in our time discounting experiment. Once again, we restrict $\beta = 1$ and $\theta = 0$.

- **Model 3:** Like Model 2, our third model is also estimated on all available time discounting data. However, the specification of Model 3 differs from Model 2 in that it allows for non-exponential discounting. The model thus requires estimation of the two behavioral discounting parameters ρ and β. As for the previous models, we assume utility to be linear in outcomes, such that $\theta = 0$.

- **Model 4:** Lastly, we estimate the most general model introduced above allowing for both non-linear utility and present bias.

Until now, we have considered a deterministic model. To incorporate the possibility of errors, we have to make an assumption about the stochastic nature of choices. To do this, we assume random utility with additively separable choice noise (McFadden 1974, 1981). Denoting S_z as the temporal points allocation arising from choice z in a specific situation, the utility of S_z is given by $U(S_z) = d(t_1)u((10-z)x_1) + d(t_2)u(z \cdot x_2)$. We presume that the utility of a temporal stream of outcomes equals $V(z) = U(S_z) + \varepsilon_z$, with ε_z being an i.i.d. random variable representing error in evaluating utility.

Under the assumption that ε_z follows a Type I extreme value distribution with (inverse) scale (precision) parameter λ and $z' \neq z$, an individual chooses allocation z if $V(z) > V(z')$. This yields the choice probability $\text{Prob}(\cdot)$ of allocation z:

$$\text{Prob}(z) = \text{Prob}(U(S_z) - U(S_{z'}) > \varepsilon_{z'} - \varepsilon_z) = \frac{e^{\lambda U(S_z)}}{\sum_{k=0}^{10} e^{\lambda U(S_k)}} .$$

We estimate the model using maximum likelihood. The objective function to be maximized is equal to

$$f(\mathcal{S};\eta) = \prod_{j=1}^{m} \prod_{k=0}^{10} \text{Prob}(z)^{1[S_z = S_k]} ,$$

where η denotes the vector of parameters to be estimated. The first product multiplies over all m choice situations in $\mathcal{S}$, and the second product multiplies over all 11 possible allocations. Note that the stochastic specification of the model introduces an additional precision parameter λ, which is constrained to be positive. $\lambda = 0$ represents random choice. In this case, choice probabilities follow a uniform distribution over the 11 possible allocations. Large λ's, on the other hand, indicate higher precision.

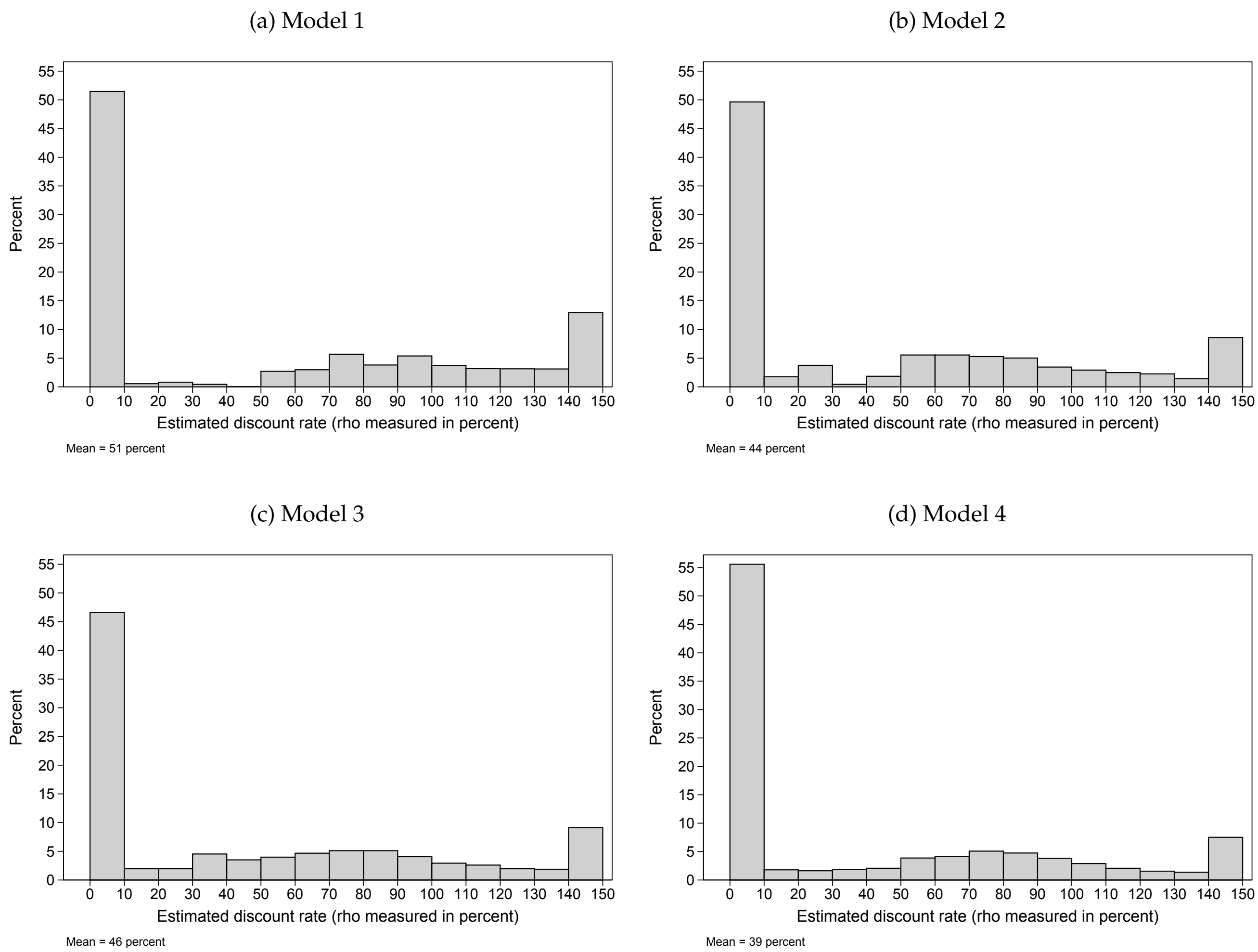
Figure A3 depicts the distribution of estimated annual discount rates for all individuals in our sample for the four different models. Subjects who always chose to save all blocks in all choice situations are included. For some subjects, the estimated annual discount rates exceed 145 percent, which is the maximum discount rate offered in the experiment, cf. Table A1. We set the actual discount rate to 145 percent for these subjects. The distributions are very similar across the four models, with a mean discount rate ranging from 39 to 51 percent per annum. This is in line with the previous literature, for example surveyed by Frederick et al. (2002).

Models 3 and 4 allow for non-constant discounting. For these models, we find that 30-40 percent of the individuals seem reasonably unbiased, defined as $\beta \in (0.95, 1.05)$, while 15 percent display present-biased behavior and 45-55 percent display future-biased behavior, i.e. there is little evidence that present bias is important. This is broadly consistent with the findings from the non-parametric measure where slightly more individuals are future biased than present biased.

In Table A2, we show that the ordering of individuals according to level of patience across models

1-4 is very similar to the ordering according to our non-parametric patience index defined in equation (4). The table shows the results from rank-rank regressions where the dependent variable is based on the patience index while the explanatory variables are based on the estimated discount rate from each of the four models. Across the models, the rank-rank coefficient is in the range 0.84-0.97.

Figure A3: Distributions of structurally estimated discount rates



Notes: The panels show distributions of structurally estimated annual discount rates. The estimated discount rates are based on four different models:
Panel a: Exponential discounting. Linear utility. Uses the five money sooner-or-later tasks that involve payments at $t_1 = 8$ weeks and $t_2 = 16$ weeks.
Panel b: Exponential discounting. Linear utility. Uses all 15 experimental time choice situations.
Panel c: Allows for non-exponential discounting. Linear utility. Uses all 15 experimental time choice situations.
Panel d: Allows for non-exponential discounting. Allows for non-linear utility. Uses all 15 experimental time choice situations.
In all four panels, estimated discount rates are censored at 145 percent, which is the maximum discount rate offered in the experiment.

Table A2: Relationship between the non-parametric patience measure and structurally estimated discount rates

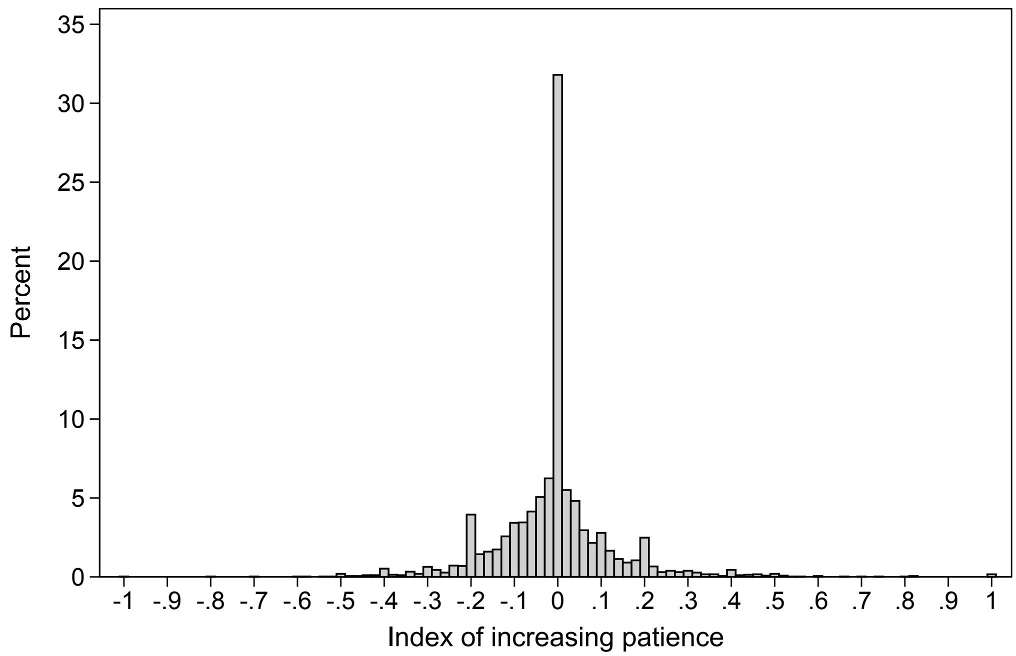
Dep. var.: Rank of non-parametric patience, 8 vs. 16 weeks	(1)	(2)	(3)	(4)
Rank of estimated discount rate, model 1	0.97			
	(0.00)			
Rank of estimated discount rate, model 2		0.89		
		(0.01)		
Rank of estimated discount rate, model 3			0.84	
			(0.01)	
Rank of estimated discount rate, model 4				0.85
				(0.01)
Observations	3,620	3,620	3,620	3,620
Adj. R-squared	0.93	0.79	0.71	0.73

Notes: OLS regressions of the ranked non-parametric patience measure on ranked estimated discount rates from models 1-4. Robust standard errors in parentheses. All regressions include constant terms (not reported).

B.4 Distribution of the non-parametric measure of non-constant time discounting

We compute the difference in savings choices between 0-8 weeks (short run) and 8-16 weeks (long run) for each of the five interest rates offered in the experiment and take the arithmetic mean of these differences for each individual. The distribution across individuals of this difference between short-run and long-run decisions is bell shaped around zero as shown in the figure below. According to this measure, individuals are on average time consistent with about 1/3 exhibiting no bias, while a little less than 1/3 of the individuals save more in the long run decisions than in the short run decisions ("present biased") and close to 1/3 of the individuals save more in the short run decisions than in the long run decisions ("future biased").

Figure A4: Distribution of increasing patience, non-parametric measure



Notes: The figure shows the distribution of the index of increasing patience. The higher the index, the more the individual has chosen to save in the 8-16 weeks situations (long run) relative to the 0-8 weeks situations (short run).

B.5 Risk task and risk aversion measure

We use investment games similar to Gneezy and Potters (1997) to measure risk aversion. The main differences to their setup are: (*i*) that we used a graphical interface to present the investment choice and (*ii*) that we varied both probabilities of winning and rates of return across the choice situations. In addition, like for all other preference elicitation tasks, we carefully explained the task with the help of animated videos. A typical choice situation is depicted in Figure A5. The left panel shows the initial state of a choice situation. The subject was endowed with ten 100-point blocks positioned at the very left of the screen and could then decide how many of these blocks to invest in a risky asset. The (binary) risky asset, depicted on the right-hand side of the choice screen, resulted in either a good outcome or a bad outcome. In the example, the good outcome occurred with probability 60 percent (illustrated by the wheel on top of the risky asset) and yielded 130 points for each invested 100-point block. The bad outcome occurred with probability 40 percent and yielded 70 points for each invested 100-point block. The user interface worked in the same way as in the time task.

Figure A5: Risk choice task

(a) Initial screen (b) Selected option

A total of 15 choice situations are implemented. They vary in terms of probabilities and rates of return. Table A3 presents a list of all choice situations in the risk task. 'vb' is the value of a block. 'm1' is the multiplier in case the good state occurs, in which case the new value of a block is vb×m1. 'm2' is the multiplier in case the bad state occurs, in which case the new value of a block is vb×m2. 'p' is the probability of the good state. 'mev' is the expected multiplier, mev $= p \times m_1 + (1-p) \times m_2$. 'msd' standard deviation of the multiplier, msd $= \sqrt{p \times (m_1 - \text{mev})^2 + (1-p) \times (m_2 - \text{mev})^2}$. 'mskew' is the skewness of the multiplier, mskew $= \frac{p \times (m_1 - \text{mev})^3 + (1-p) \times (m_2 - \text{mev})^3}{\text{msd}^3}$. 'slope' is the slope of the budgets, i.e. the ratio of prices, $slope = \frac{m_2 - 1}{m_1 - 1}$.

Like in the other tasks, choice situations in the risk task appear in individualized random order. If the random choice situation picked in the payment stage is a risky choice situation, the subject is again confronted with her choice. The choice can not be reverted at this stage, however. The subject is then asked to resolve uncertainty in the present situation. This is done by spinning the wheel on top of the risky asset. The final payout corresponds to the sum of the safe account and the resolved outcome of the originally risky account. Payments are transferred directly to subjects' NemKonto on the next banking day.

We construct the risk aversion index as follows: We take all choice situations with zero skewness, i.e. with probability 0.5 (choiceId 1, 4, 7, 14 and 15 in Table A3). We then normalize and aggregate using the arithmetic mean:

Table A3: Risk choice situations

choiceId	vb	m1	m2	p	mev	msd	mskew	slope
1	100	1.21	0.81	0.5	1.010	0.200	0.000	-0.905
2	100	1.41	0.91	0.2	1.010	0.200	1.500	-0.220
3	100	1.11	0.61	0.8	1.010	0.200	-1.500	-3.545
4	100	1.31	0.71	0.5	1.010	0.300	0.000	-0.935
5	100	1.61	0.86	0.2	1.010	0.300	1.500	-0.230
6	100	1.16	0.41	0.8	1.010	0.300	-1.500	-3.688
7	100	1.35	0.75	0.5	1.050	0.300	0.000	-0.714
8	100	1.65	0.90	0.2	1.050	0.300	1.500	-0.154
9	100	1.20	0.45	0.8	1.050	0.300	-1.500	-2.750
10	100	1.50	0.40	0.6	1.060	0.539	-0.408	-1.200
11	100	1.72	0.62	0.4	1.060	0.539	0.408	-0.528
12	100	1.45	0.35	0.6	1.010	0.539	-0.408	-1.444
13	100	1.67	0.57	0.4	1.010	0.539	0.408	-0.642
14	100	1.51	0.50	0.5	1.005	0.505	0.000	-0.980
15	100	1.61	0.60	0.5	1.105	0.505	0.000	-0.656

$$\phi_{\text{risk aversion}} = \text{mean}\left(\frac{z_1}{10}, \frac{z_4}{10}, \frac{z_7}{10}, \frac{z_{14}}{10}, \frac{z_{15}}{10}\right),$$

where z_i denotes the number of blocks kept in the safe account in choice situation i. $\phi_{\text{risk aversion}}$ is an index of risk aversion with $\phi_{\text{risk aversion}} \in [0, 1]$. Higher values of $\phi_{\text{risk aversion}}$ indicate greater risk aversion, and a $\phi_{\text{risk aversion}}$ of zero indicates minimum risk aversion.

B.6 Social preference task and altruism measure

We use dictator games to measure altruism. In each choice situation, the subject (dictator) chose one out of eleven allocations of points between her-/himself and an anonymous person (the recipient). The recipient took part in another session of our study, but did not make choices as a dictator. Dictators and recipients were randomly matched, and they remained anonymous to each other at all points in time. Possible allocations were displayed using a graphical interface. The cost of increasing or decreasing the recipient's payoff varied across the different choice situations. Figure A6 depicts a typical choice situation as it was presented to dictators. The left panel illustrates the initial screen in that choice situation with no allocation yet selected. Once the dictator picked the preferred option, a blue bar appeared around the selected option. The right panel of the figure illustrates the situation in which allocation 5 was chosen.

Figure A6: Social preference task

(a) Initial screen

(b) Selected option

12 choice situations were implemented. Table A4 presents the list of all choice situations in the social preference task. $(\text{own}_1, \text{other}_1)$ refers to the allocation on top of the choice screen, and $(\text{own}_2, \text{other}_2)$ refers to the allocation on the bottom of the choice screen. The budget lines for the choice situations have slope $= \frac{\text{other}_2 - \text{other}_1}{\text{own}_2 - \text{own}_1}$. The choice situation presented in Figure A6 corresponds to choiceId 4 in Table A4.

Table A4: Choice situations in social preference task

choiceId	own_1	other_1	own_2	other_2	slope
1	1,050	550	450	950	-0.667
2	1,000	500	500	1,000	-1.000
3	950	450	550	1,050	-1.500
4	900	450	600	1,050	-2.000
5	850	450	650	1,050	-3.000
6	850	400	650	1,100	-3.500
7	800	400	700	1,100	-7.000
8	750	400	750	1,100	∞
9	700	400	800	1,100	7.000
10	700	450	800	1,050	6.000
11	650	400	850	1,100	3.500
12	650	450	850	1,050	3.000

Like in the other tasks, choice situations in the social preference task appeared in individualized random order. If the random choice situation picked in the payment stage was from the set of social preference tasks, the subject was informed about her choice in that situation. The choice could not be reverted at this stage, however. The subject (dictator) and the other person (recipient) received the respective amounts in the chosen allocation. Payments were transferred directly to people's NemKonto.

We construct an altruism index as follows: We take all choice situations with negative slope (choiceId 1 to 7 in Table A4) and aggregate using the arithmetic mean. We define:

$$\phi_{\text{altruism}} = \text{mean}\left(z_1, ..., z_7\right) ,$$

where $z_i \in [0, 1]$ denotes the allocation $(\text{own}, \text{other})$ in choice situation i. $z_i = 0$ is the allocation on top of the choice screen, and $z_i = 1$ is the allocation on the bottom of the choice screen. Thus, higher values of z_i means giving more to the recipient.

Specifically, $(\text{own}, \text{other}) = ((1 - z_i)\text{own}_1 + z_i\text{own}_2, (1 - z_i)\text{other}_1 + z_i\text{other}_2)$. ϕ_{altruism} is an index of costly altruism with $\phi_{\text{altruism}} \in [0, 1]$. Higher values of ϕ_{altruism} indicate greater altruism, and a ϕ_{altruism} of zero indicates minimum altruism (maximum selfishness).

B.7 Respondents vs. non-respondents

Table A5 provides summary statistics for our respondents (column a) and non-respondents (column b) and their differences (column c). The respondents are slightly older, less likely to be single and slightly more educated compared to non-respondents. Wealth and income of the respondents are higher throughout the distributions.

Table A5: Means of selected characteristics. Respondents vs. non-respondents

	(a) Respondents	(b) Non-respondents	(c) (a)-(b)	
Age	37.32	36.46	0.86	(0.00)
Woman (=1)	0.50	0.49	0.00	(0.74)
Single (=1)	0.28	0.38	-0.10	(0.00)
Dependent children (=1)	0.70	0.64	0.06	(0.00)
Years of education	14.90	14.17	0.73	(0.00)
Gross income distribution				
p5	135,745	98,974	36,772	
p25	287,472	234,953	52,520	
p50	382,997	341,621	41,376	(0.00)
p75	484,463	434,679	49,784	
p95	719,754	655,002	64,752	
Wealth distribution				
p5	-337,615	-351,123	13,507	
p25	93,899	48,894	45,006	
p50	486,006	317,455	168,551	(0.00)
p75	1,066,468	800,084	266,385	
p95	2,395,664	2,024,448	371,216	
Observations	3,620	23,624	27,244	

Notes: Variables are based on 2015 values. P-values from unconditional t-tests of equality of means in parentheses. The reported p-values for the gross income distribution and the wealth distribution are from two-sample Kolmogorov-Smirnov tests for equality of distribution functions. (=1) indicates a dummy variable taking the value 1 for individuals who satisfy the description given by the variable name. Wealth denotes the value of real estate, deposits, stocks, bonds, mortgage deeds in deposit, cars and pension accounts minus all debt except debt to private persons. The tax assessed values of housing is adjusted by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Gross income refers to annual income and excludes capital income. Wealth and income are measured in Danish kroner (DKK). The table includes individuals for whom a full set of register variables is available.

C Empirical results

C.1 Association between individual discount rates and wealth levels

Appendix B.3 provides estimates of individual discount rates based on four different random utility models. Below we display the results from regressing wealth levels on these measures of impatience. Columns 1-4 show that the association between wealth levels and discount rates is in the range DKK -918 to DKK -720 per percentage point across the different models. Columns 5-8 show that a one standard deviation higher discount rate is associated with a DKK 38,700-46,900 lower level of wealth.

Table A6: Relationship between wealth in amounts and structurally estimated discount rates

Dep. var.: Wealth in amounts (1,000 DKK)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification:	——Discount rates in percent——				—Standardized discount rates—			
Discount rate, model 1	-0.720				-41.5			
	(0.175)				(10.1)			
Discount rate, model 2		-0.918				-46.9		
		(0.192)				(9.8)		
Discount rate, model 3			-0.845				-43.4	
			(0.196)				(10.0)	
Discount rate, model 4				-0.774				-38.7
				(0.196)				(9.8)
Age dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,620	3,620	3,620	3,620	3,620	3,620	3,620	3,620
Adj. R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

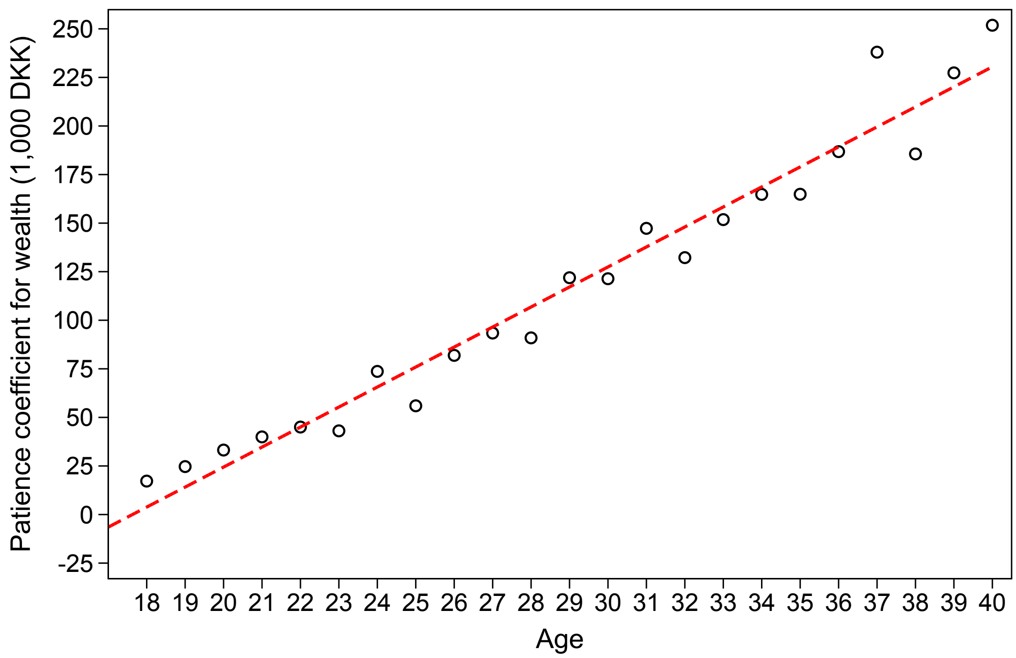
Notes: OLS regressions of wealth measured in amounts (1,000 DKK) in 2015 on structurally estimated annual discount rates from four different models. Robust standard errors in parentheses. Columns 1-4 regress on the estimated discount rates per se, whereas columns 5-8 regress on standardized values of discount rates. All regressions include age indicators to account for life-cycle patterns and constant terms (not reported). Model 1: Exponential discounting. Linear utility. Uses the five money sooner-or-later tasks that involve payments at t1 = 8 weeks and t2 = 16 weeks. Model 2: Exponential discounting. Linear utility. Uses all 15 experimental time choice situations. Model 3: Allows for non-exponential discounting. Linear utility. Uses all 15 experimental time choice situations. Model 4: Allows for non-exponential discounting. Allows for non-linear utility. Uses all 15 experimental time choice situations. Estimated discount rates are censored at 145 percent in all four models, which is the maximum annualized interest rate offered in the experiment. As the discount rates used in these regressions are estimated, the standard errors in the regressions are potentially underestimated. Ideally, standard errors should be bootstrapped. However, the computational burden of estimating the discount rates is already immense. Bootstrapping with a reasonable number of replications is therefore not practically feasible.

C.2 Additional evidence on the association between savings and patience

This appendix provides two additional pieces of evidence on the association between savings and patience. First, Figure A7 shows the relationship between patience and wealth against age in our data. The points in the graph show the regression coefficients from age-specific regressions of wealth measured in DKK on patience. The straight line indicates how these coefficients rise with age (the slope of the straight line is the parameter on the interaction between patience and age in a regression of wealth on patience and age). The slope is DKK 10,301 with a 95% confidence interval of [DKK 7,396; DKK 13,205], indicating how patience drives wealth accumulation as age progresses.

Second, we calculate the savings rate across the period 2001-2015, i.e. $\frac{wealth_{2015}-wealth_{2001}}{income_{2015}}$, as well as the annual savings rate, i.e. $\frac{wealth_t-wealth_{t-1}}{income_t}$, across the period 2002-2015. The results are reported in columns (1) and (2) in Table A7. Column (1) reports the long savings rate estimate. It indicates that when going from the lowest to the highest level of patience in the sample then savings are 47 percent of an annual income higher. Column 2 presents the estimate based on the annual savings rate. The result shows that annual savings increase by about 2.4 percent of an annual income when going from the least patient to the most patient individual in the sample.

Figure A7: Relationship between patience and wealth over age



Notes: The points in the graph show the regression coefficients from age-specific regressions of wealth measured in amounts (1,000 DKK) on patience. The straight line indicates how these coefficients increase with age. The slope of the straight line represents the parameter on the interaction between patience and age in a regression of wealth on patience, age indicators, and the interaction between patience and age). The slope is DKK 10,301 with a 95% confidence interval of [DKK 7,396; DKK 13,205], indicating that the role of patience on wealth levels increases as age progresses. Each age group is given the same weight when superimposing the straight line.

Table A7: Patience and savings rate

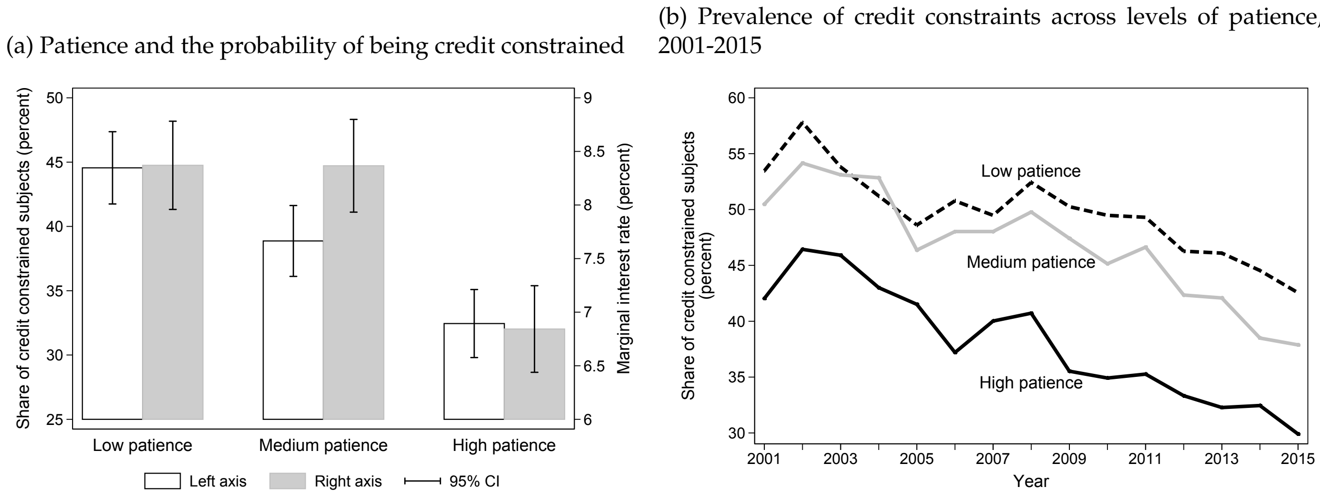
Dep. var.: Savings rate	(1) Savings rate, 2001-2015	(2) Annual savings rate, 2002-2015
Patience	0.470	0.024
	(0.111)	(0.009)
Risk aversion	0.201	0.019
	(0.131)	(0.012)
Educational attainment	Yes	Yes
Additional controls	Yes	Yes
Year dummies	No	Yes
Observations	3,544	49,077
Adj. R-squared	0.05	0.02

Notes: OLS regressions of the savings rate on patience. In column 1, the savings rate is defined as $\frac{wealth_{2015}-wealth_{2001}}{income_{2015}}$. Robust standard errors in parentheses. Column 2 includes annual data for the period 2001-2015. Here, the savings rate is defined as $\frac{wealth_t-wealth_{t-1}}{income_t}$,where $t = 2002, ..., 2015$. Standard errors are clustered at the individual level in column 2. In both specifications of the savings rate, income refers to gross annual income and excludes capital income. Savings rates are winsorized at p1 and p99 within cohorts. The additional controls include the same control variables as column 3 in Table 2, panel B. However, column 2 in the current table with annual data does not include decile indicators based on the observed income growth from age 25-27 to age 30-32 or decile indicators for the expected income growth from 2014 to 2016 obtained from survey information accompanying the experiment. Both regressions include constant terms (not reported).

C.3 Association between patience and the propensity to be credit constrained

Figure A8 displays the association between patience and the two measures of credit constraints described in Section IIID. Panel a shows that patient individuals tend to be less credit constrained than impatient individuals according to both measures. Panel b shows that the cross-sectional relationship between patience levels and the propensity to be credit constrained is stable over the period 2001-2015. The panel also shows that the propensity to be observed with low levels of liquid assets generally declines for all three patience groups over time. This reflects the fact that people in the sample are in the early stages of their life cycle and accumulate more assets as they grow older.

Figure A8: Association between time discounting and propensity to be credit constrained



Notes: The figures show the association between elicited patience and different measures of credit constraints. The sample is split into three equally sized groups according to the tertiles of the patience measure such that “High patience” includes the 33 percent most patient individuals in the sample, “Low patience” the 33 percent most impatient individuals and “Medium patience” the group in between the “High patience” and “Low patience” groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. In panel a, the white bars show the association between elicited patience and the propensity to hold liquid assets worth less than one month’s disposable income in 2014. The grey bars show the association between elicited patience and the marginal interest rate in 2014 for the three patience groups. Panel b shows the association between elicited patience and the share of individuals within each patience group who are observed with liquid assets corresponding to less than one month’s disposable income in the period 2001-2015.

C.4 Marginal interest rates

Here we present details about the construction of marginal interest rates. We obtained access to administrative register data from the Danish tax authority containing information on the value of loans at the end of 2013 and 2014 for all loans that the respondents held in Denmark. In addition, the data comprise interest payments during 2014 at the individual loan level. This allows us to approximate the interest rate paid on each loan as $r_{i,l} = \frac{R_{i,l}^{14}}{\frac{1}{2}(D_{i,l}^{13}+D_{i,l}^{14})}$, where $R_{i,l}^{14}$ is the sum of interest payments on loan l for individual i during 2014, $D_{i,l}^{13}$ is the value of the loan at the end of 2013, and $D_{i,l}^{14}$ is the value of the loan at the end of 2014. We only include non-mortgage loans and require a minimum denominator in the above equation of DKK 1,000. The resulting interest rates are censored at percentiles 5 and 95. Our approximation of the interest rate is exact if the debt evolves linearly between 2013 and 2014. If it does not, the computation of the interest rate may introduce a measurement error.

For respondents with loan accounts, we define the marginal interest rate as the highest calculated loan account-specific interest rate. If a respondent only has deposit accounts, we define the marginal interest rate as the smallest account-specific interest rate among the calculated account-specific interest rates for that respondent. The rationale is that the cost of liquidity is given by the loan account with the highest interest rate if a respondent has loan accounts, whereas the cost of liquidity for a respondent who only has deposit accounts is determined by the account where the lowest return is earned. Table A8 shows the distribution of the computed marginal interest rates.

Table A8: Distribution of marginal interest rates

Percentile	p5	p25	p50	p75	p95
Marginal interest rate	0.00	0.97	6.25	12.73	22.82

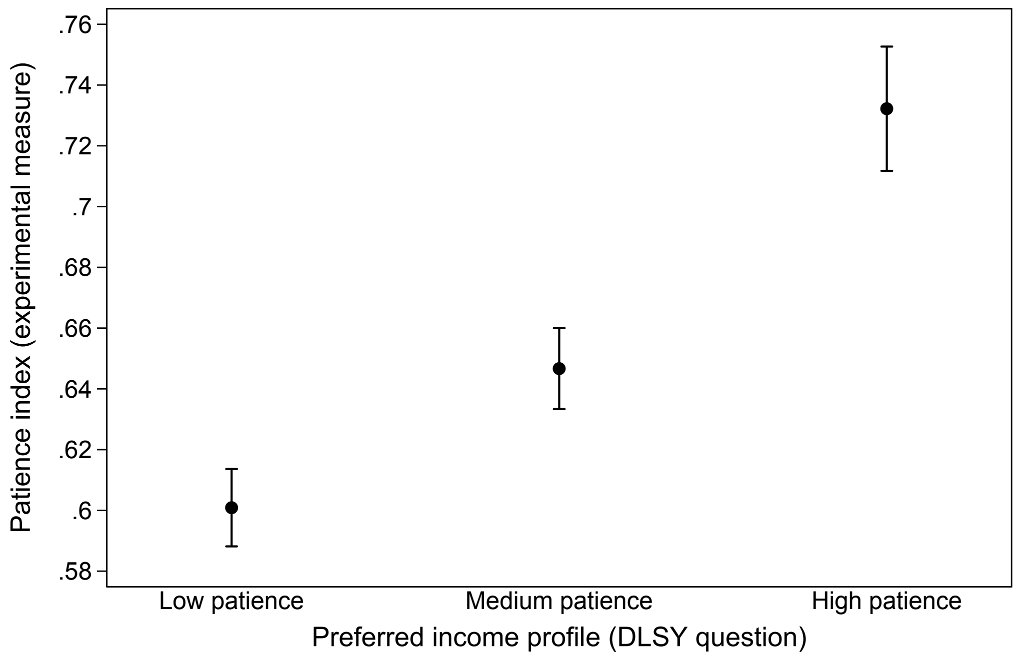
D Importance of reverse causality, selection and measurement

D.1 Comparing patience measured in the DLSY survey and in the experiment

In this appendix, we compare patience elicited with the DLSY survey questions to the patience elicited in the experiment. We do this with data from a large-scale online study conducted during the year 2018. 4,151 Danes of the cohorts with birth year 1967 to 1986 completed the study. In addition to the DLSY survey measure described in Section IVA, the study also included our intertemporal choice task with real monetary incentives. With the exception that there were 100 blocks instead of 10 to be allocated between two points in time in each of the choice situations, the intertemporal choice task was identical to that described in Section II. For comparability, we bin the 100 blocks into 10 and then construct our patience index based on the $t_1 = 8$ weeks vs. $t_2 = 16$ weeks allocations.

Figure A9 depicts the average (dots) of our patience index conditional on the three possible responses in the DLSY question and 95 percent confidence intervals (whiskers). It shows that responses in the DLSY question and choices in the incentivized, intertemporal choice task are highly and significantly correlated.

Figure A9: Comparison of DLSY and experimental measure

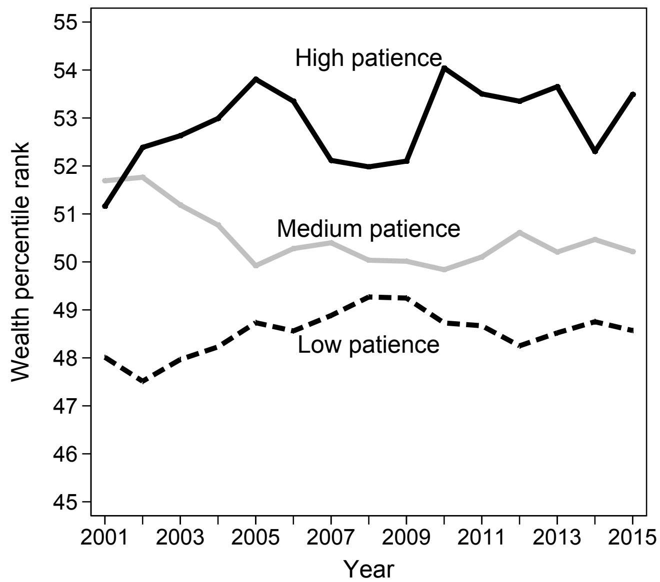


Notes: This figure presents a binned scatterplot displaying, for each category of the DLSY measure, the average of the patience index based on the experiment together with the 95 percent confidence interval.

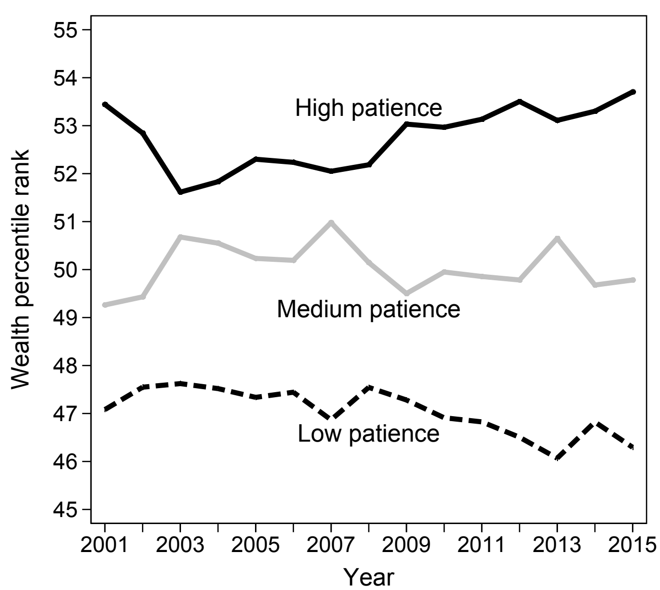
To further corroborate the evidence about the stable relationship between the two measures and wealth inequality, we have reproduced panel A of Figure 3 and the corresponding survey-based version, panel A of Figure 6, for the 2,096 respondents from the 2015 experimental sample where we have both patience based on the experiment and based on the survey question that was used in the original 1973 DLSY. The result is displayed in the figure below. The top panel is based on the survey question and the bottom panel is based on the experimental measure. The two figures both show a very stable wealth rank ordering across the three patience groups. The levels are generally similar across the two panels, even though the impatient group according to the survey measure is perhaps ranked slightly higher than the impatient group according to the experimental measure.

Figure A10: Survey and experimental measures of patience and position in the wealth distribution 2001-2015 in the experimental sample

(a) Split by preferred income profile question (DLSY style)



(b) Split according to the experimental measure



Notes: In a follow-up study including 2,096 respondents from the main experiment, we aked the survey question on preferred income profile that was also used in the 1973 Danish Longitudinal Survey of Youth. Panel a shows the association between time discounting elicited as in the DLSY and the position in the wealth distribution in the period 2001-2015. Three groups are defined based on the answers to the question: *If given the offer between the three following jobs, which one would you choose? (i) A job with an average salary from the start.* ["Low patience"] *(ii) A job with low salary the first two years but high salary later.* ["Medium patience"] *(iii) A job with very low salary the first four years but later very high salary.* ["High patience"] Panel b shows the association between experimentally elicited patience and the position in the wealth distribution in the period 2001-2015. The sample is split into three patience groups according to the patience measure. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. In both panels, the position in the wealth distribution is computed as the within cohort×time percentile rank in the sample.

D.2 Measurement and selection

In the main analysis, our patience measure is based on the subset of choice tasks where the subjects were asked to choose between payouts 8 and 16 weeks from the experiment date. As described in Section B.2, we also confronted subjects with trade-offs that involved payouts made as soon as possible after the experiment, where the delay only pertained to the time required to administer the transfer to the participant's account. In Table A9, we construct patience measures based on all possible combinations of the payment dates that we exposed subjects to ("today", "in 8 weeks" and "in 16 weeks"). Row 1 reproduces Table 2, column 1 (without controls) and column 3 (with controls). Rows 2-3 in Table A9 present estimates based on regressions where the patience measure is based on alternative choice situation horizons. The parameter estimates on patience are stable across these regressions. Row 4 omits observations for individuals always postponing the payouts, and also here the parameter on patience is significant and not statistically distinguishable from the baseline specification in row 1. In the final row we use the rank of the structurally estimated discount rate, cf. Appendix B.3, as our patience measure. Also in this case are the estimates practically identical to the estimates for the baseline specification, cf. row 1.[1]

Table A9: Patience and wealth inequality. Other patience measures

Dep. var.: Wealth percentile rank Patience measure:	(1) No controls	(2) With controls
1. Non-parametric, 8 vs. 16 weeks	11.37	8.45
	(1.73)	(1.75)
2. Non-parametric, 0 vs. 16 weeks	11.79	8.83
	(1.88)	(1.90)
3. Non-parametric, 0 vs. 8 weeks	11.80	8.88
	(1.78)	(1.81)
4. Non-parametric, 8 vs. 16 weeks, $\neq 1$	8.90	7.11
	(2.25)	(2.26)
5. Rank of estimated discount rate	10.52	7.85
	(1.66)	(1.67)

Notes: OLS regressions of within-cohort wealth percentile rank on patience measures and other covariates. The table shows estimated coefficients for various measures of patience. Robust standard errors in parentheses. The specification "With controls" includes the same control variables as column 3 in Table 2. All regressions include constant terms (not reported). "Non-parametric, 8 vs. 16 weeks" is the standard measure referred to as "Patience" in the other tables and figures. In row 4, "$\neq 1$" indicates that individuals who always postpone in the choice situations are omitted. The rank of estimated discount rates in row 5 ranges from 0 to 1 to be comparable to the non-parametric measures of patience. In this row, a higher rank means a lower estimated discount rate. The ranking of estimated discount rates is based on model 1 defined in Appendix B.3. The number of observations is 3,620 in the "No controls" specefication and 3,552 in the "With controls" specification. However, in the row "Non-parametric, 8 vs. 16 weeks, $\neq 1$", the number of observations is 2,943 and 2,895, respectively.

[1] Since the discount rate in this regression is estimated, the standard errors in the regression are potentially underestimated. Ideally, standard errors should be bootstrapped. However, the computational burden of estimating the discount rates is already immense. Bootstrapping with a reasonable number of replications is therefore not practically feasible.

Table A10 provides a number of additional robustness checks. For convenience, row 1 displays the results from the baseline specification, cf. Table 2, column 1 (without controls) and column 3 (with controls). Row 2 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. This is done to account for the fact that the tax assessed values may be somewhat below market values (Leth-Petersen 2010). The estimate of the patience parameter attenuates slightly but the parameter is precisely estimated and is within one standard deviations from the reference estimate in row 1. The wealth data including housing and financial wealth are consistently third-party reported for an exceptionally long period. However, they lack two components of wealth that are potentially important for assessing wealth inequality, wealth kept in the car stock and wealth accumulated in pension accounts. Data documenting these two components has recently become available, but only from 2014 onwards. In row 3, we include the value of the car stock among assets and calculate the net wealth rank based on 2015 data. The patience parameter is close to the estimate in row 1. We further include wealth kept in pension accounts in row 4. This addition slightly mutes the point estimate of the patience parameter. There are good reasons why adding pension wealth would attenuate the estimate. 90 percent of contributions to pension accounts are made to illiquid employer organized pension accounts (Kreiner et al. 2017), and the contributions are predominantly determined by collective labor market agreements. As Chetty et al. (2014*a*) document, the majority responds passively to these savings mandates, i.e. they do not adjust other types of savings in response to these savings mandates.

In the experiment we have collected information about patience for individuals and not all adult household members. Wealth is, however, arguable accumulated jointly in the household. In row 5, we have reproduced the baseline specification using housheold level wealth as the basis of the wealth rank. The results are practically unaffected by this change.

An important subcomponent of wealth is liquid financial wealth, including deposits, stocks and bonds. In row 6, we use liquid financial wealth as the basis for calculating the wealth rank. In this case the results indicate an even stronger association between patience and the wealth rank.

The theory posits that wealth transfers from parents can be a confounder. In the baseline specification, we control flexibly for parental wealth. However, we do not see actual transfers in the data. In order to assess whether this is likely to confound the results, we re-estimate the baseline specification for the subsample of individuals where both parents are alive. The most important transfer from parents to children is likely to take place when parents die and pass on bequest. If both parents are alive such transfers have not yet been materialized. The results in row 7 are practically identical to the baseline specification.

Only a fraction of the subjects whom we invited to participate in the experiment accepted the invitation, and this can potentially imply that our sample is selected and not representative of the population at large. In row 8, we re-estimate the reference specification from row 1 using propensity score weighting, where the propensity scores measure the propensity to participate in the experiment for all the subjects who were invited. The propensity scores are estimated using variables created from information available in the administrative registries accessible for both participants and non-participants: year dummies for educational attainment, decile dummies for income, observed income growth, parental wealth and wealth at age 18 as well as age dummies, a gender dummy, a dummy for being single and a dummy for having dependent children. The results are close to the estimate from the reference specification. In row 9, we construct propensity scores measuring the propensity to be in the experiment compared to the population at large. As with previous cases, we find no important deviations from the benchmark model. The propensity score weighting approach is based on the assumption that the selection into the experiment can be adequately captured by the set of covariates on which the propensity score is estimated. To the extent that this is a reasonable assumption, our results do not appear too specific to the sample for which we elicit patience measures.

Table A10: Patience and wealth inequality. Robustness analyses

Dep. var.: Wealth percentile rank Specification of Wealth:	(1) No controls	(2) With controls
1. Wealth, 2015	11.37	8.45
	(1.73)	(1.75)
2. Wealth, adjusted housing value	11.24	7.05
	(1.72)	(1.69)
3. Wealth, adjusted housing value + car value	11.05	6.79
	(1.73)	(1.68)
4. Wealth, adjusted housing value + car value + pension wealth	9.93	5.24
	(1.74)	(1.51)
5. Wealth, household level	11.03	8.25
	(1.72)	(1.75)
6. Financial assets	16.82	9.91
	(1.70)	(1.55)
7. Wealth, both parents alive	10.99	8.54
	(2.18)	(2.21)
8. Wealth, IPW: respondents vs. non-respondents	9.76	7.10
	(1.76)	(1.78)
9. Wealth, IPW: respondents vs. population	10.00	7.17
	(1.86)	(1.85)

Notes: OLS regressions of within-cohort wealth percentile rank on the patience measure and other covariates. The table shows estimated coefficients for the patience measure. Robust standard errors in parentheses. The specification "With controls" includes the same control variables as column 3 in Table 2. All regressions include constant terms (not reported). Row 1 reproduces the regressions in columns 1 and 3 from Table 2. Row 2 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Row 3 includes the value of the car stock. Row 4 includes both the value of the car stock and wealth held in pension accounts. In row 5, the dependent variable is constructed on the baseline wealth measure (as in row 1), but the within-cohort wealth percentile rank is computed at the household level instead of at the individual level. Row 6 considers only financial assets, ie. stocks, bonds and deposits. Row 7 uses the baseline wealth measure, but the estimations are based on the subset of observations where the respondents' parents are both still alive. In row 8, the dependent variable is constructed on the baseline wealth measure, but the equation is estimated using inverse probability weighting where probability weights are based on respondents vs. non-respondents. Row 9 presents results for the baseline wealth measure estimated using inverse probability weighting where the weights are based on respondents vs. population. The number of observations is 3,620 in the "No controls" column and 3,552 in the "With controls" column. However, in row 7, the sample is restricted to individuals with both parents alive, which reduces the number of observations to 2,367 and 2,335, respectively. Furthermore, in the "No controls" column in rows 8 and 9, the number of observations is 3,573, as the inverse probability weighting requires that all variables used to construct the weights are observable.

Table A11 presents a number of additional robustness checks. Again, row 1 displays the results from the baseline specification, cf. Table 2, column 1 (without controls) and column 3 (with controls). In row 2, we allow for a categorization of educational attainment consisting of 59 categories representing educational subject areas (e.g. "comparative literature studies", "economics" and "physics"). In this way we allow, for example, for the possibility that a degree in literature has a different return than a degree in physics. This does not change the estimated parameter on patience.

In rows 3-5, we calculate the wealth rank and income deciles based on averages over 2013-2015, 2011-

2015 and 2009-2015, respectively. Across all these cases, the estimated patience parameter is essentially identical. In row 6 we condition on being in the labor force every year in the period 2011-2015 and not experiencing unemployment in the period 2011-2015, with wealth rank and income deciles based on 2015. Again, the patience parameter is very close to the baseline specification. In row 7 we condition on having a stable relationship status (no spouse or same spouse) in the five-year period 2011-2015. The wealth rank and income deciles are based on 2015. The patience parameter is now slightly lower than in the other rows but is still precisely estimated and within one standard deviation from any of the patience estimates in the other rows. Finally, we restrict the sample to respondents whose socioeconomic status did not indicate poor health in the period 2008-2015, but this does not affect the estimated parameter in any important way either.

Table A11: Patience and wealth inequality. Robustness analyses

Dep. var.: Wealth percentile rank Specification:	(1) No controls	(2) With controls
1. Wealth 2015, income 2015	11.37	8.45
	(1.73)	(1.75)
2. Wealth 2015, income 2015, 59 educational groups	11.37	8.33
	(1.73)	(1.77)
3. Wealth 2013-2015, income 2013-2015	11.16	8.60
	(1.74)	(1.76)
4. Wealth 2011-2015, income 2011-2015	11.32	8.61
	(1.74)	(1.76)
5. Wealth 2009-2015, income 2009-2015	11.51	9.04
	(1.75)	(1.76)
6. Wealth 2015, income 2015, in the labor force every year 2011-2015,	11.64	8.61
no unemployment 2011-2015	(2.32)	(2.34)
7. Wealth 2015, income 2015, stable relationship status 2011-2015	9.73	7.17
	(1.95)	(1.97)
8. Wealth 2015, income 2015, good health 2008-2015	11.00	7.95
	(1.94)	(1.96)

Notes: OLS regressions of within-cohort wealth percentile rank on the patience measure and other covariates. The table shows estimated coefficients for the patience measure. Robust standard errors in parentheses. The specification "With controls" includes the same control variables as column 3 in Table 2. All regressions include constant terms (not reported). Row 1 reproduces the regressions in columns 1 and 3 from Table 2. Row 2 controls flexibly for education by including indicators for 59 general educational groups instead of indicators for years of schooling. "Comparative literature studies", "economics" and "physics" are examples of general educational groups. Row 3 includes wealth rank (dependent variable) and income deciles computed within cohorts based on averages over 2013-2015, row 4 is similar, but wealth rank and income deciles are based on averages over 2011-2015 and in row 5, the two variables are based on averages over 2009-2015. Row 6 uses the baseline specification, but the estimations are based on the subset of respondents who were in the labor force every year in the period 2011-2015, and who were never unemployed in the period 2011-2015. Row 7 uses the baseline specification, but restricts the sample to respondents who had a stable relationship status (i.e. no spouse or the same spouse) in the period 2011-2015. Row 8 also uses the baseline specification, but restricts the sample to respondents whose socioeconomic status did not indicate poor health in the period 2008-2015. The number of observations is 3,620 in the "No controls" column and 3,552 in the "With controls" column. However, in row 6, that conditions on labor force participation and no unemployment, the number of observations is 2,265 and 2,243, respectively. In row 7 that conditions on stable relationship status, the number of observations is 2,704 and 2,651, respectively. Furthermore, row 8 that conditions on good health has 3,030 and 2,987 observations, respectively.

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