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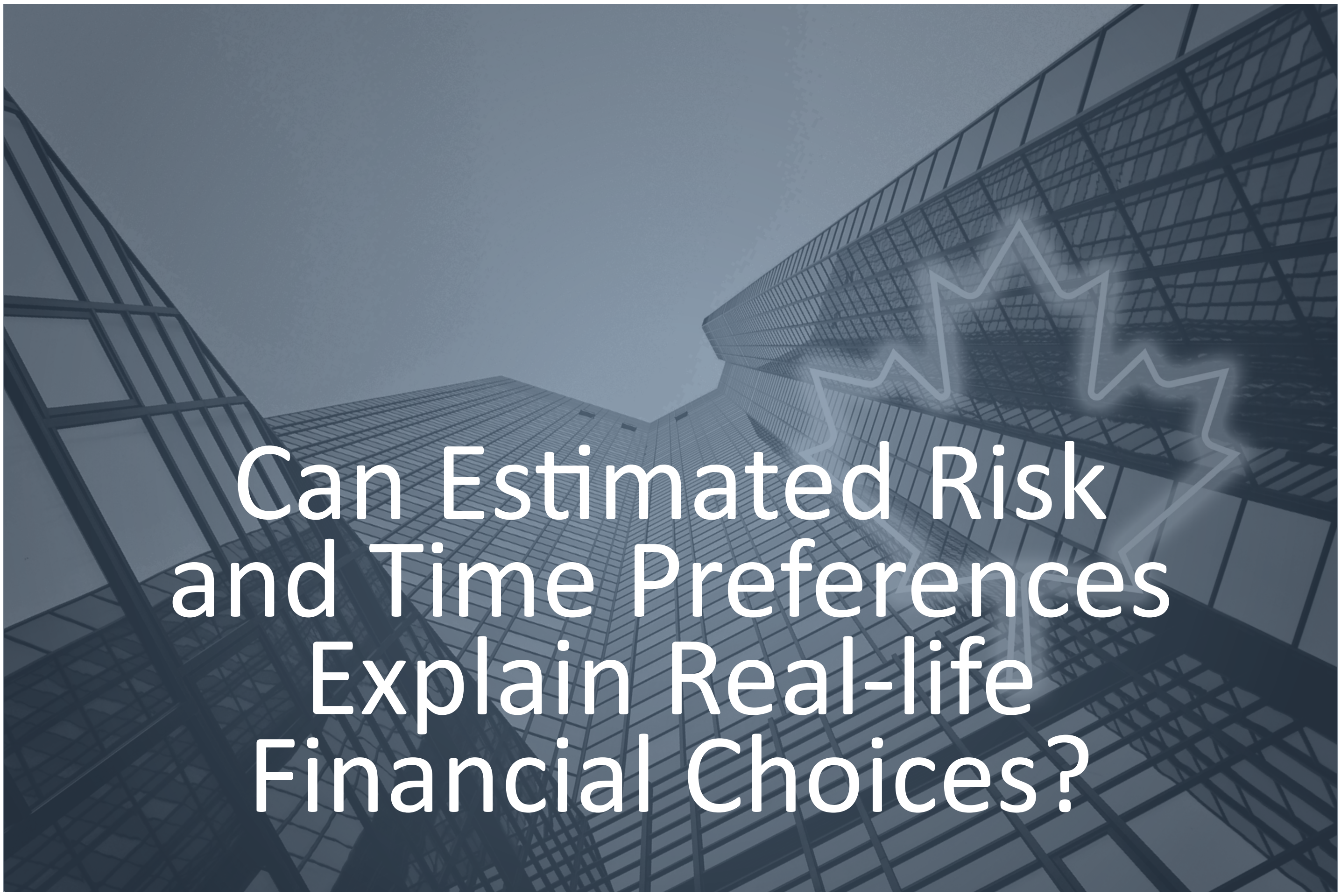

Can Estimated Risk and Time Preferences Explain Real-life Financial Choices?

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ABOUT THIS REPORT:

We combine experimentally elicited preferences with administrative micro data to study actual financial decision-making. Firstly, we estimate risk and (present-biased) time preferences in a real-life context, with horizons up to 10 years, for a large group of pension fund participants. We estimate a present-bias factor of 0.88, an annual discount rate of 3.91% and a CRRA utility curvature of 0.97. Secondly, using a life-cycle framework, we show that the individually estimated preferences explain actual retirement decisions up to 83% of our sample. Freedom of choice creates annual welfare gains up to 4.8%, but realized welfare gains are lower or even negative.

Can Estimated Risk and Time Preferences Explain Real-life Financial Choices?*

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September 28, 2020

Abstract

We combine experimentally elicited preferences with administrative micro data to study actual financial decision-making. Firstly, we estimate risk and (present-biased) time preferences in a real-life context, with horizons up to 10 years, for a large group of pension fund participants. We estimate a present-bias factor of 0.88, an annual discount rate of 3.91% and a CRRA utility curvature of 0.97. Secondly, using a life-cycle framework, we show that the individually estimated preferences explain actual retirement decisions up to 83% of our sample. Freedom of choice creates annual welfare gains up to 4.8%, but realized welfare gains are lower or even negative.

Keywords: behavioral economics, life-cycle model, risk and time preferences, real-life choices, decision making

JEL Codes: D01, D03, D12, D14, D80, D91, G02, G11

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Risk and time preferences play a role in almost every economic decision. As a consequence, understanding individual risk and time preferences is key in the design of welfare enhancing policies and pension schemes. Over the past decades, researchers have been studying risk and time preferences. On the one hand, there is a need to measure risk and time preferences among distinct groups and across domains. On the other hand, it remains an empirical question how estimated preferences relate to actual behavior and the corresponding welfare effects.

In the literature, much attention has been devoted to estimating present bias, annual discounting and risk preferences. However, there remain three unresolved questions. First of all, it is unclear how structurally estimated risk and time preferences in a high-stakes real-life context with long decision horizons compare to the previous literature. The second question is how structurally estimated preferences relate to personal characteristics and, more interestingly, whether preferences can explain actual economic behavior. Thirdly, since we find that actual behavior can be explained by structurally estimated risk and time preferences, we can investigate the welfare effect of flexibility in the payout phase of pension schemes.

In this paper, we address these three questions by eliciting risk and time preferences among pension fund participants that make actual annuitization decisions. We jointly estimate risk and time preferences by the Convex Time Budgets method of Andreoni and Sprenger (2012a). We use a large-scale non-student sample of 1100 pension fund participants. The experiment is in a real-life pension context, where the pension participants experimentally allocate €10,000 (11,800 USD) for long horizons up to 10 years. Therefore, we can expect individuals to spend more effort in thinking about their choice than in a laboratory with small stakes, no pension context and short horizons.

Consequently, given the individually estimated preferences, we use a detailed individual dataset with personal characteristics to study the determinants of mainly present bias, and annual discounting and CRRA risk preferences. The dataset also includes the real-life annuitization decision of retirees, such that we can study to what extent risk and time preferences explain actual financial decision making. Rather than the frequently observed linear correlations, we also use a structural (non-linear) life-cycle model to determine how preferences influence the retirement choice. We study such economic behavior in the context of present bias, because it appears intuitive that present-biased individuals are tempted to withdraw more pension wealth immediately at retirement. Finally, using the life-cycle model, we quantify the welfare implications of freedom of choice that is offered through the choice between a flat annuity and a flexible annuity with many lumpsum characteristics.

The Dutch pension fund's data has several advantages compared to other data sources. Firstly, the dataset includes actual real-life pension choices rather than incentives or attitudes on economic decision making. Secondly, it provides detailed and reliable information on the participants and pension plan, which is hard to ask in surveys. As a consequence, we can distinguish expected payment schemes on life expectancy that is *fund* specific to age and gender. Thirdly, the annuity decision involves large stakes with long decision horizons, identical to our experiment on risk and time preferences. Finally, the Dutch annuity choices reflect many pension choices globally, since worldwide lumpsum possibilities are offered.

Our results imply for the quasi-hyperbolic discounting model (also known as the $\beta - \delta$ model) a present-bias factor of 0.88, an annual discount rate of almost 3.91% and a CRRA utility function curvature of 0.97. We find (significant) evidence for present bias since the present-bias factor $\beta < 1$, which is consistent with the general finding of substantial present bias in the literature (Frederick et al., 2002). The estimated curvature of the CRRA utility function is (significantly) different from linear utility but remains close to linear and, thus, similar to previous findings. Note that classical risk aversion estimates tend to deviate more from linear utility.

Our risk and (present-biased) time preference estimates are comparable to previous estimates in the literature. This is interesting in itself, because many previous studies that jointly estimate the utility function and time discounting use laboratories without a specific context based on student samples. Only our estimated discount rate is lower than previously found. The estimated annual discount rate is in line with market interest rates and appears more plausible than estimates in previous research, where estimates of annual discount rates from 30%-100% are not uncommon (Frederick et al., 2002; Andreoni and Sprenger, 2012a; Cheung, 2020). Potential reasons of our plausible estimated discount rate are the magnitude of the experimental budget and the long-term decision horizons (Thaler, 1981). Namely, laboratory experiments typically have short decision horizons that run from several weeks to several months (Andersen et al., 2010; Tanaka et al., 2010; Augenblick et al., 2015), but do not exceed more than 3 years (Harrison et al., 2002; Goda et al., 2015). Moreover, the typical experimental payment equals tens of dollars (Andreoni and Sprenger, 2012a), rather than ten thousand dollars.

The second set of results shows that our individually estimated risk and (present-biased) time preferences explain real-life financial decisions to a large extent. We find that (near) time-consistent individuals indeed chose a flat annuity, while present-biased individuals chose a flexible annuity to withdraw more pension wealth during the early years of retirement. Furthermore, we use a life-cycle expected utility model to explain individuals' choices for a flat or flexible annuity, where the latter has many lumpsum characteristics. For error margin of 5% certainty equivalent consumption, similar to the interpretation of a 95% confidence interval, risk and (present-biased) time preferences explain the annuitization decisions for 83% of our population of retirees. Additionally, we find in a multivariate analysis that the present-bias factor correlates positively with males, age, private savings and a proxy for education level with correlations up to 0.094.

To our knowledge, no previous paper has related jointly estimated risk and (present-biased) time preferences to actual financial decision making by means of a (non-linear) life-cycle model. Most papers rather assess how predictive preferences are by correlations from multivariate linear regression analysis (Cohen et al., 2020). Dohmen et al. (2010) relate time preferences to cognitive ability. Chabris et al. (2008) show that the correlations for health behavior (e.g., BMI, smoking, exercise) and financial behavior (saving, gambling) are statistically indistinguishable from zero with behavior on time preference tasks.

Tanaka et al. (2010) found that higher patience correlates with higher income. Furthermore, implicit in laboratory elicited preferences is the assumption that laboratory results are a reliable assessment of general behavior, even though we know that the typical subject pool is different from the population to which they are being applied (Andersen et al., 2010). We overcome this problem by eliciting preferences and observing behavior directly in the same population.

Finally, given the success of predicting behavior by risk and (present-biased) time preferences, we perform a welfare analysis to investigate the effects of introducing freedom of choice. Specifically, we quantify the welfare effects of the flexible annuity option, because it tends to be chosen mainly by present-biased individuals and, as such, policy makers might find the observations useful. The potential welfare gain of freedom of choice, by means of a flexible annuity, is on average 2.90-4.79% while the realized welfare gain is only 0.62%-1.70% in terms of annual certainty equivalent consumption. Interestingly, high educated individuals and higher income groups realize most of the welfare gains, while the low educated and the low income individuals suffer welfare losses due to freedom of choice. To improve welfare, policy makers can possibly help those individuals by improving choice architecture and communication.

I. Experimental design

We implement the method of Convex Time Budgets (Andreoni and Sprenger, 2012a; Andreoni and Sprenger, 2012b) at a large pension fund in The Netherlands, together with a present-bias task.

A. Convex Time Budgets

Subjects choose an amount c_t, available at time t, and an amount c_{t+k}, available after a delay of $k > 0$ periods, continuously along a convex budget set

$$c_t + \frac{c_{t+k}}{1+r} = m, \tag{1}$$

where $(1+r)$ is the experimental gross interest rate and m is the experimental budget. The Convex Time Budgets (CTB) method asks subjects to maximize some utility function $U(c_t, c_{t+k})$.

In our CTB task, subjects face 20 convex budget decisions. Following Potters et al. (2016), the starting time t is always one year from the experiment date and the delay length k equals 10 years. The delay length is relatively long and selected such that we can study decision making under uncertainty for long horizons. The likelihood that the later payment is actually paid out, depends on the decision set. A (4×5) design was implemented with four later payment probabilities $p_{t+k} = (0.5, 0.7, 0.9, 1.0)$ and five varying interest rates per probability. These 20 budgets involved 20 varying annual interest rates from 0 to 8.40 percent per year. Thus, there are four decision sets based on the probability of late payment, and within each set are five CTB scenarios with varying interest rates.

In each CTB scenario, subjects are given a budget m of €10,000. Money allocated to the early payment has a value of c_t, while money allocated to the late payment has a present value of $c_{t+k}/(1+r)$. In some scenarios, the late payment is uncertain with probability p_{t+k}. For instance, when p_{t+k} is 0.7, then the late payment is paid out with a chance of 70%, and nothing is paid out with a chance of 30%. c_{t+k}/c_t defines the gross interest rate $1+r$ over k years, so $(1+r)^{1/k} - 1$ gives the standardized annual interest rate r. Multiplication by the payment probability p_{t+k} defines the risk-adjusted interest rates.

Table 1 shows the starting time, delays, payment probabilities and interest rates for the 20 scenarios in the Convex Time Budgets task. The timing of payments with delay length k identifies time preferences, while sensitivity to changing the gross interest rates $1+r$ delivers identification of risk preferences. The advantage of the CTB method is a simultaneous measurement of time and risk preferences. For this reason, we avoid the assumption of linear utility and, consequently, we avoid upward-biased discount rate estimates if true utility is concave (Andersen et al., 2008; Noor, 2009).

To identify potential present bias, we implement a task in our experiment from the INTRA (International Test of Risk Attitudes) study, conducted by the University of Zurich.[1] This task is an adapted version from the question in Frederick (2005), and reads as follows:

> *Enter an amount c_1 such that option B is as attractive as option A:*
> A. Receive €800 now,
> B. Receive € c_1 next year.

Subjects have to make a trade-off between a direct payment of €800 now or a later certain payment c_1 next year. Due to the implementation of an immediate payment now combined with the long-run decisions from the Convex Time Budgets, we can elicit and estimate the present bias for every subject. Table 1, scenario 21, summarizes the present-bias task.[2]

B. Implementation

Our experiment was conducted at the pension fund ABP (National Civil Pension Fund) in The Netherlands.[3] The pension fund has a large panel for experimental research and communicates via email. In order to participate in our experiment, pension fund participants in this panel between the ages of 50 and 70 years were recruited. The recruitment process for our experiment and the experiment itself were simultaneously in the period 13 August 2018 till 17 September 2018. Participants could join the experiment by clicking on a link in the email. 1110 pension fund participants joined the experiment.

The experiment is part of a larger survey from the pension fund. The first part of the survey asks subjects for personal information, such as pension attitudes, demographics (age, education) and financial situation (income, housing wealth). Then, the second part of the survey contains our experiment. Subjects could go through the survey, including experiment, at their own pace,

[1] Another possibility to measure present bias would have been by varying the starting times t in the CTB method.

[2] The original question is in US dollars, so the monetary payoff in our scenario is adjusted according to the currency exchange rate and Purchasing Power Parity (PPP) in The Netherlands.

[3] ABP is the Dutch abbreviation for "Algemeen Burgerlijk Pensioenfonds" and it is the largest pension fund in The Netherlands, mainly for civil servants such as government and education employees.

also going back and forth through the questions.

In the email, and at the end of the survey, we announce that subjects are able to receive one out of five vouchers with a value of €50. The voucher will be received via email, implying that subjects need to enter their email address. Our experiment is not incentivized, based on the experimental answers of the subjects. Some researchers argue that incentives in economic experiments lead to more truthful reveal of preferences. However, according to the overview of Cohen et al., 2020, in the literature there seems to be little evidence for systematic differences between incentivized and unincentivized experiments. Another review by Camerer and Hogarth (1999) finds that incentives do not reliably change average performance, but tend to decrease the variance of responses. Since our sample is relatively large, this decreases the variance of the preference estimates on an aggregate level. Furthermore, Potters et al. (2016) find no difference between incentivized and unincentivized choices. Moreover, our hypothetical choice situation avoids the need for (complex) equalization of payments, transaction costs and corresponding payment confidence.

A Qualtrics program was written to implement the survey, including our experiment in the second part. Upon starting the experiment, subjects read through the instructions and a CTB example decision screen. The CTB example indicated to the subjects that the budget could be entirely allocated to the early payment (corner), entirely to the later payment (corner) or divided between the two (interior). The percentage of responses that are at corners equals 46%, but the number of subjects that made zero interior allocations is only 8%. These percentages might seem high at first sight, but are low compared with the literature. Andreoni and Sprenger (2012a) find that "roughly 70 percent of responses are at corners, but only 36 of 97 subjects [37%] made zero interior allocations."

Figure 1 shows an image of a decision screen. The decision screen contains a timeline of the payment structure: 2018 is the experimental date, the early payment is in 2019 at starting time t and the late payment is in 2029 after an additional delay of $k = 10$ years. Subjects are told to divide the amount of €10,000 between the early payment c_t and late payment c_{t+k}. Probabilities of late payment and interest rates were highlighted by yellow and blue, respectively. The likelihood that the late payment is paid equals $p_{t+k} = 100\%$ in this particular decision screen. The subject has to make five budget decisions presented in order of increasing interest rates from 1.00 to 1.59 in the five scenarios. Subjects are faced with a total of four decision screens, corresponding to the four probability decision sets. After the CTB task, the present-bias task follows.

C. Sample

This section describes the sample, based on the information available from the pension fund and the pre-experiment questionnaire. We have observations from 1110 pension fund participants. 705 respondents are ative participants, who actively accrue pension rights at the pension fund ABP through their employer. 405 respondents are retirees, who receive pension benefits from the pension fund.

Table 2 compares our sample of subjects with the pension fund's population from 2018, restricted to the ages of 50 and 70.[4] Panel A shows that the male to female and active to retiree ratios are nearly equal. Because we focus on retirees only for the real-life choice part of the paper, we present detailed summary statistics on the retired population in Panel B. The median age of our retired subjects is 67.02 years, which is close to the pension fund's value. Our male respondents are more likely to have a somewhat higher income, but the female income is nearly identical to the pension fund's value.[5]

II. Results

In this section, we firstly describe the aggregate behavior in the CTB and present-bias tasks. Then, we discuss the parameter estimation of individual

[4] We focus on old-age pension for the pension fund's retirees.

[5] Table 10 in Online Appendix B provides detailed summary statistics on demographic, financial and pension variables. Tables 11 and 12 in Online Appendix B describe the definitions of all variables used in our analysis.

risk and (present-biased) time preferences. We end with preference estimates and correlations with personal characteristics.

A. Descriptive analysis

Figure 2a summarizes aggregate choice behavior in the present-bias task, for active and retired respondents. The upper panel reports the allocated amount c_1 in Euros that makes subjects indifferent between receiving €800 now or c_1 next year. The dashed red bars depict retirees, while the solid gray bars depict active participants. Retirees allocate lower amounts of wealth c_1 to next year, while active participants allocate higher amounts of wealth c_1 to next year to make them indifferent with €800 directly.

The bottom panel reports the implied annual interest rates based on the allocated amounts c_1. For at least 77% (69%) of the active participants (retirees), the observed interest rates from the present-bias task are substantially larger than the interest rates in the CTB task, which vary from 0 to 8.40 percent per year by design. Thus, in line with Thaler (1981), we find that short-term discount rates over 1 year are (much) higher than long-term discount rates over 10 years.[6] This observation provides evidence for time inconsistency and indicates the possibility of present bias on aggregate for pension fund participants. More specifically, the distribution shows that active participants are more subject to time inconsistent behavior than retirees. The effect is visible between the lower interest rates of 0% to 20%, where the fraction of retirees is higher, while for interest rates larger than 20% the fraction of active participants is higher.

Figure 2b summarizes aggregate choice behavior in the CTB task for active and retired respondents combined. We plot the median allocated Euros chosen at the early payment c_t against the gross interest rate $(1 + r)$, of each CTB decision for each separate probability of late payment p_{t+k}. The amount of Euros allocated to the early payment declines monotonically with the interest rate, indicating that people wait for the late payment when interest rates

[6] A decision period of 1 year is arguably short in terms of pension planning.

are higher. Additionally, as expected, the amount of earlier Euros increases when the late payment probability is lower. So, Figure 2b reveals that choices respond to changing interest rates and payment probabilities in a predicted way.

Although masked by these aggregate results, individual heterogeneity is important. The next section discusses the parameter estimation and individual estimates.

B. Estimating preference parameters

We identify experimental allocations as solutions to standard intertemporal optimization problems. These solutions are supposed to be functions of our parameters of interest (present bias, discounting and curvature), and experimentally varied parameters (interest rates, delay lengths and payment probabilities). Given assumptions on the functional form of utility and the nature of discounting, our experimental tasks provide a natural context in which to jointly estimate individual present bias, discount rate and curvature.

Using the quasi-hyperbolic $\beta - \delta$ model of intertemporal decision making (Phelps and Pollak, 1968; Laibson, 1997), the subject maximizes *discounted expected utility* over the early payment c_t and late payment c_{t+k}

$$\begin{aligned} \max_{c_t, c_{t+k}} \delta^t \left[p_t U(c_t + w_1) + (1 - p_t) U(w_1) \right] \\ + \beta \delta^{t+k} \left[p_{t+k} U(c_{t+k} + w_2) + (1 - p_{t+k}) U(w_2) \right], \end{aligned} \tag{2}$$

where δ is the one period discount factor and β is the present-bias factor. The quasi-hyperbolic form captures the notion of time-inconsistent behavior, since $\beta < 1$ indicates present bias. Moreover, it nests exponential discounting (i.e. standard time-consistent behavior, Samuelson, 1937) when $\beta = 1$. The values c_t and c_{t+k} (including interest) are the experimentally allocated payments, and p_t and p_{t+k} are the corresponding probabilities of payment. The terms w_1 and w_2 are additional utility parameters which could be interpreted as background consumption or income (see e.g. Andersen et al., 2008). Background consumption is frequently assumed to be zero in many experimental studies, but could also be estimated or fixed at the individual's reported income level.

We posit the agent has a time separable Constant Relative Risk Aversion (CRRA) utility function of the form

$$U(x) = \frac{1}{\alpha}x^{\alpha}, \tag{3}$$

where α is the curvature of the CRRA utility function. It is important to precisely distinguish with the CRRA utility function that at times is formulated as

$$U(x) = \frac{1}{1-\gamma}x^{1-\gamma}, \tag{4}$$

with γ the coefficient of relative risk aversion parameter of the individual.[7]

Under *discounted utility*, $\alpha < 1$ implies concavity of instantaneous utility that captures resistance to intertemporal substitution, giving rise to a preference to smooth payoffs over time. Under *expected utility*, $\gamma > 0, \gamma \neq 1$ implies concavity that captures classical risk aversion, giving rise to a preference for more equally-distributed payoffs over states of nature. In principle, risk aversion and intertemporal substitution describe conceptually distinct preferences (Cheung, 2020). But, in our experimental setting, both risk and time are present, such that it is common to assume that utility for risk is the same as instantaneous utility for time. This gives rise to *discounted expected utility*.[8]

However, another important distinction is the source of identification for concavity in the discounted and expected utility models. In our CTB task, sensitivity to changing interest rates delivers identification of the concavity of the utility function (risk preferences), while variation in the timing of payments identifies the discounting parameters β (present bias) and δ (time preferences). Since our CTB task asks to allocate payments throughout time for changing

[7]This is equivalent to our formulation with $\alpha = 1 - \gamma$.

[8]In the literature, we find that concavity under discounted utility (i.e. over time) is less than concavity under expected utility (i.e. under risk), but curvature estimates significantly differ from linear utility as well (for example, see Andreoni and Sprenger, 2012a).

interest rates, we identify curvature, rather than risk aversion, based on the degree of price sensitivity in intertemporal choice. Essentially, we ask the subject about the smoothness of payoffs over time.[9]

Solving the subject's standard intertemporal maximization problem (2) subject to the budget constraint (1) yields the first-order condition:

$$\left(\frac{c_t + w_1}{c_{t+k} + w_2}\right)^{\alpha-1} = \beta\delta^k(1+r)\frac{p_{t+k}}{p_t}. \tag{5}$$

Notice that indeed the experimental answers depend (non linearly) on the parameters of interest (present bias, discounting and curvature), as well as the experimentally varied parameters (interest rates, delay length and payment probabilities).

Taking the natural logarithm, and using the fact that in our design the early payment is certain, such that $p_t = 1$, we find

$$\begin{aligned} \ln\left(\frac{c_t + w_1}{c_{t+k} + w_2}\right) = &\left(\left(\frac{\ln\beta}{\alpha-1}\right) + \left(\frac{\ln\delta}{\alpha-1}\right)\cdot k\right)\cdot \mathbb{1}_{p_{t+k}=1} \\ &+ \left(\frac{1}{\alpha-1}\right)\cdot\left(\ln(1+r) + \ln(p_{t+k})\right), \end{aligned} \tag{6}$$

where $\mathbb{1}_{p_{t+k}=1}$ is an indicator function for a certain probability of late payment. Because the present-bias task concerns a certain payment directly or a certain payment next year, we consistently estimate present bias and discounting only in combination with CTB scenarios for certain late payments. For this reason, our time-preference estimates are not directly affected by the payment probabilities, but only the curvature estimate of the utility function.

Since the gross interest rate $1 + r$ and payment probability p_{t+k} vary, it identifies the CRRA curvature parameter α. However, the starting time t and delay length k are fixed in our CTB design, such that we cannot distinguish between the present-bias factor and long-term discount factor. Therefore, we use the present-bias task to identify the present-bias factor β and the discount

[9] Alternatively, we could have identified concavity of the utility function by a risky choice task, such as in Holt and Laury (2002). Then, due to the other source of identification, concavity gives rise to the classical risk aversion interpretation.

factor δ, while simultaneously correcting for potential curvature α.

Again using the quasi-hyperbolic discount model and CRRA utility function (3), the subject in the present-bias task solves

$$U(800 + w_0; \alpha) = \beta \cdot \delta \cdot U(c_1 + w_1; \alpha). \tag{7}$$

In words, the subject considers a trade-off between a direct early payment of €800 at $t = 0$, or a (discounted) payment c_1 one year later at $t = 1$. Solving explicitly for the present-bias factor yields

$$\beta = \frac{1}{\delta} \left(\frac{800 + w_0}{c_1 + w_1} \right)^{\alpha}. \tag{8}$$

Notice that the present-bias factor depends on the experimental answer c_1 (and background consumption), and is separated from the long-term discount factor with a simultaneous correction for curvature. So, substituting β, we can write regression equation (6) explicitly as

$$\begin{aligned} \ln\left(\frac{c_t + w_1}{c_{t+k} + w_2}\right) = {} & \left(\left(\frac{\alpha}{\alpha - 1}\right) \cdot \ln\left(\frac{800 + w_0}{c_1 + w_1}\right) + \left(\frac{\ln \delta}{\alpha - 1}\right) \cdot (k - 1) \right) \cdot \mathbb{1}_{p_{t+k}=1} \\ & + \left(\frac{1}{\alpha - 1}\right) \cdot \left(\ln(1 + r) + \ln(p_{t+k})\right). \end{aligned} \tag{9}$$

Given an additive error structure and known non-estimated values for background consumption, such a linear equation is easily estimated with parameter estimates for α, δ, β obtained via nonlinear combinations of coefficient estimates. Equation (9) shows clearly that the curvature α is identified by changing interest rates and payment probabilities, while present bias β and discounting δ are identified by the delay length k and the present-bias task c_1 (for certain payments only), while simultaneously being corrected for curvature.

C. Preferences and correlations

Table 3 presents estimates of present bias, discounting and CRRA curvature parameters at the individual level. For each subject, we estimate the preference parameters by equations (8) and (9) and, then, we compute summary statistics. We show results for all pension fund participants, and for retirees and active participants separately. To limit the number of estimated parameters, and facilitate comparison with previous literature, we restrict $w_0 = w_1 = w_2 = 0.01$.[10] We estimate the parameters $\hat{\beta}, \hat{\delta}, \hat{\alpha}$ by two-limit Tobit and OLS.

Firstly, echoing the results in Figure 2a, we find evidence of present bias. We estimate the median and mean present-bias factor $\hat{\beta}$ respectively at 0.878 and 0.868 with a tight standard error of 0.007. Moreover, active pension fund participants are more subject to present bias than retirees. The absolute difference in present-bias factors between active participants and retirees equals 0.056 (0.049) at the median (mean).

The general finding in the literature is a (substantial) present bias (Frederick et al., 2002; Tanaka et al., 2010; Laibson et al., 2015). Our estimated present-bias value is similar to those estimated by other researchers. Balakrishnan et al. (2017) also use the CTB design also in a monetary experiment, and find present-bias estimates ranging from 0.902 to 0.924. Other papers have used nonmonetary experiments such as job search for estimating discounting behavior. Paserman (2008) estimates a present-bias factor of 0.8937 for high income workers, which is in line with our sample of high income participants. DellaVigna and Paserman (2005) often find a present-bias factor near 0.9. Using experiments on real effort tasks, Augenblick et al. (2015) and Augenblick and Rabin (2019) present a present-bias factor ranging from 0.83 to 0.89.

Secondly, the estimated annual discount factor $\hat{\delta}$ has an average value of 0.967 with a standard error of 0.005. Differences between active participants and retirees are negligible. An estimate of the annual discount rate follows from $(1/\hat{\delta}) - 1$. Thus, the annual factor implies an annual discount rate of

[10] The idea is that subjects do not integrate the experimental payments with background income. Essentially, we assume a form of mental accounting: one account for the experimental payments, and one for the participant's regular income.

approximately 4%. This value is in line with (long-term) market interest rates and lower than most previous studies. Estimates of annual discount rates over hundred percent are not uncommon, as illustrated by the overview article of Frederick et al. (2002). Cheung (2020) estimates an annual discount rate of 62.6%, when controlling for CRRA curvature. The CTB design of Andreoni and Sprenger (2012a) corrects for CRRA curvature and present bias, but they still estimate an annual discount rate of 27.5%. A close estimate is that of Andersen et al. (2014), who report an annual discount rate of 7.3% in the quasi-hyperbolic model, while controlling for (classical) risk aversion.

A potential reason for our highly plausible annual discount rate is the magnitude of the experimental budget and the long-term decision horizon. Thaler (1981) shows that discount rates drop sharply as the size of wealth increases, which is known as the magnitude effect, and he reports that discount rates drop sharply as the length of time increase. We confirm both findings in our large non-student sample. The experimental budget of €10,000, combined with the decision horizon of 10 years, are both (much) larger than many of the previous studies. Horizons are frequently used up to several weeks (Augenblick et al., 2015), 3 months (Tanaka et al., 2010), 6 months (Andersen et al., 2010), 1 year (Dohmen et al., 2010; Andersen et al., 2014), 2 years (Goda et al., 2015) and 3 years (Harrison et al., 2002).

A paper that comes close to ours in terms of large stakes and long decision horizons is Potters et al. (2016), who use an experimental budget of €1,000 with a decision horizon up to retirement age. They report an annual discount rate of 1% in line with our estimate. Another reason might be that not all previous studies correct for utility curvature when estimating time preferences, such that discount rates might be upward biased (Andreoni and Sprenger, 2012a). However, based on high income workers, Paserman (2008) estimates a yearly discount factor of 0.9989 not corrected for curvature.

The third finding is that the average CRRA curvature $\hat{\alpha}$ is 0.938 with a median of 0.966. Curvature estimates for active participants and retirees are identical at the median. Since the CRRA curvature estimate is < 1, with a tight standard error of 0.004, we can conclude that utility is concave. However, the CRRA curvature comes much closer to linear utility than estimates of classical risk aversion, as employed by Holt and Laury (2002) and Eckel and Grossman (2008). Our finding is in line with previous research on CRRA curvature estimates, such as Andreoni and Sprenger (2012a) and Potters et al. (2016). Notice that OLS and TOBIT parameter estimates are extremely similar for all preferences and participants. For this reason, corner solutions do not seem to be a major issue.

Figure 3 shows the distribution of present bias, discounting and curvature from the subjects in our experiment. Clearly, there is individual heterogeneity in risk and (present-biased) time preferences. We winsorize the parameter estimates $\hat{\beta}, \hat{\delta}, \hat{\alpha}$ at a 5% level such that we do not have to discard these observations in our analysis, but for this reason we observe a higher fraction of subjects at the boundaries of the distribution.

The top panel shows that the majority of pension fund participants is present biased since $\hat{\beta} < 1$, and specifically active participants are more subject to present bias than retirees. Notice that nearly 23% of our sample is future biased, meaning that $\hat{\beta} > 1$. This percentage is similar to 19% of future biased subjects in the sample of Bleichrodt et al. (2016). Also, Andersen et al. (2014) observe future biased participants. The middle panel shows that a majority of the subjects has reasonable annual discount factors between 0.8 and 1.0, implying a maximum annual discount rate of 25%. But, a portion of our sample has long-term negative annual discount rates, where $\hat{\delta} > 1$, such that these participants are extremely patient (i.e. they are willing to pay, rather than generate interest, to receive a payment in the future).

The bottom panel shows that nearly all subjects have a concave utility function, because $\hat{\alpha} < 1$. In other words, our participants have a preference to smooth payoffs over time. A minority has a convex utility function, which implies that these participants are risk seeking and do not prefer to smooth payoffs over time. The distributions of annual discounting and CRRA curvature are nearly identical for active participants and retirees.

Correlations

The final step of this section concerns the relation between socio-demographic factors and present bias.[11] First of all, we present bivariate relations and, secondly, we conduct a multivariate analysis that controls for more variables.

Figure 4 shows the link between demographic variables and individual present-bias factor estimates. We investigate five demographic variables: gender, partner, age, education and (self-reported) life expectancy. Additionally, we indicate the fraction of participants who fall in a particular demographic category.

The top left panel shows that there is a significant gap between males and females in present bias. Females are on average, and at the median, more present biased than males. The gap is supported by a two-sided Mann-Whitney test with a p-value < 0.01. The top right panel shows that there is no economic and statistical significant difference in present bias between those with a partner and those who are single.

The middle left panel depicts the relation between age and present bias. Clearly, as one becomes older, one becomes less present biased. The economic median difference in the present-bias factor between age ≤ 55 (0.83) and age ≥ 65 (0.91) is large (0.08), and is supported by statistical significance (Spearmann rank correlation test, p-value < 0.01). There is a positive relationship between education and present-bias factor.[12] Notice that these are correlations and no causalities, such that we cannot distinguish whether higher education decreases present bias, or because you are less present biased you pursue higher (and longer) education. The economic difference is similar to that of age, and supported by a Spearmann rank correlation test (p-value < 0.05). We do not find a relation between (self-reported) life expectancy and present bias in the bottom panel.

Figure 5 shows the relation between four financial variables and individual

[11] We analyzed relations with discounting and curvature also, but we find no economic and statistical significant relations worth mentioning.

[12] ≤ 2 is low education (primary or secondary school), while 5 is a university degree. See Tables 11 and 12 in Online Appendix B for a more detailed description of the variables.

present-bias factor estimates. The northwest panel shows a U-shaped pattern for (annual before tax) income with strong economic differences.[13] Low incomes ≤€19.999 (close to the minimum wage level) are economically less subject to present bias than higher incomes (but not significantly), except for the high incomes at the other end of the distribution. Private savings are strongly positive and significantly correlated with present bias, as shown in the northeast panel. Individuals with private savings ≤€5,000 have a present bias of approximately 0.8, while individuals with private savings ≥€50.001 have an estimated present bias of at least 0.9.

The two bottom panels show that homeowners are less present biased than tenants, and those without any mortgage(s) are less present biased. Economic median differences equal respectively 0.06 and 0.05, and are both supported by two-sided Mann-Whitney tests.

Table 4 shows regressions with the individually estimated present-bias factor as dependent variable, and demographic and financial variables as regressors. We estimate 3 models using OLS with robust standard errors. Each regression model includes an intercept, and controls for the time taken to complete the survey (duration) and the reported difficulty of the survey. In model (1) we include demographic variables, and we find that older people are less present biased. If an individual becomes 10 years older, then the present-bias factor increases on average by 0.04 ceteris paribus (somewhat smaller in magnitude than in the bivariate analysis). The age effect is interesting, because it may affect financial decision making across the life span. We observe no effects on gender and education.

Model (2) includes financial variables. Dummies for the higher private savings' categories have a positive sign and a significant relation with the present-bias factor. Especially the economic effect of higher private savings is large (e.g., 'savings 50k+' increases the present-bias factor by 0.094 on average), which contradicts the finding of insignificant near zero correlations as reported by Chabris et al. (2008). Income is positively correlated with the

[13] Table 9 presents an overview of tax as fraction of income in the Netherlands for active participants and retirees.

present-bias factor, but not significant as in the bivariate analysis. In model (3) we include both demographic and financial variables. Signs and significance levels remain similar to models (1) and (2), however gender becomes statistically significant. Moreover, low education increases present bias, but the result is insignificant. Interestingly, in all regression models the coefficient for a 'very difficult' survey is (significantly and economically) negative, while individuals who perceived the survey as 'easy' have a positive (significant and economic) coefficient. Difficulty may proxy for education, because an individual that experiences the survey as 'easy' is less present biased, while 'very difficult' increases present bias.

III. Real-life choices

This section uses administrative micro data from the pension fund to study actual annuitization decisions of the retirees ($N = 405$) in relation to their individually estimated preferences. The combination of the administrative data on actual decision making with the experimental survey is a unique feature of our research. We first study how predictive preferences are for financial decision making by using a life-cycle model. Secondly, we quantify the welfare effects of freedom of choice in annuitization decisions by studying flexibility in the payout phase of pension schemes.

The Dutch pension system has two main pillars, a publicly financed pay-as-you-go scheme and a mandatory occupational pension scheme. The *first* pillar, or General Old-Age Pensions Act (AOW), aims at providing a minimum retirement income, and is funded from tax revenues. The statutory retirement age is 66 in 2018. The majority of the active participants with an uninterrupted working career qualify for a benefit close to the maximum yearly amount of €14,000 for single individuals and roughly €18,000 for couples. First pillar benefits are indexed based on price inflation, and always paid-out as life-long annuities.

The *second* pillar is an employer-based, occupational pension scheme that features collectivity, mandatory participation and is not-for profit. Pension funds operate on the basis of capital funding: an employee, together with their employer, accrues pension entitlements from the contributions paid in and the return realized by the pension fund over the years through the collective investment of these contributions. The main goal is to maintain the pre-retirement living standards, together with the benefits from the first pillar.

When an individual retires, the pension fund offers once the possibility to withdraw the accumulated capital either as a *flat* monthly life-long annuity or as a *flexible* monthly life-long annuity. A flexible annuity is comparable to a lump sum as it allows the beneficiary to receive pension payments earlier and higher compared to a flat annuity (by means of an actuarially fair reduction in the level of future benefits). The fund's annuitization decision has two key components, and the individual must make an active choice about (i) early retirement with or without bridging pension and (ii) high-low or low-high payments.[14] If the individual foregoes to make an active choice, then the fund offers him by default a flat monthly life-long annuity starting from the statutory retirement age. At least 6 months before reaching the statutory retirement age the individual receives a notification and information from the fund about his annuitization decision (unless a choice is already made).

Regarding key decision (i), early retirement decreases overall monthly life-long benefits (at an actuarially fair rate), because the individual starts to withdraw his pension wealth earlier than the statutory retirement age. Additionally, the pension fund offers a scheme that allows the beneficiary to receive a bridging pension until the statutory retirement age is reached and, thus, the eligibility for first pillar pension benefits. The goal of a bridging pension, when retiring early, is to ensure a flat payment stream of benefits. Again, the individual depletes his second pillar pension wealth faster, so that (again) overall monthly life-long benefits are reduced (at an actuarially fair rate).

Regarding key decision (ii), the fund additionally offers once the possibility to increase benefits for 5 to 10 years at any point during the retirement phase,

[14]There is also the possibility to exchange partner pension with old-age pension, but we exclude this in our analysis because we study individual decisions. Furthermore, it is possible to retire later, but in our sample no retiree actually chose later retirement than the statutory retirement age.

key component (ii). The idea of high-low (or low-high) payments is to tailor pension benefits to the individual's needs such as paying off his mortgage (or facilitating later unexpected health costs). A high-low payment structure depletes second pillar pension wealth faster and reduces future monthly lifelong benefits (at an actuarially fair rate), while a low-high structure backloads the future benefits.[15]

In our analysis, we study whether the chosen *payment structure* (rather than annuity type) of an individual is flat or flexible. In nearly all cases, a payment structure is flexible if an individual opted for a high-low (or low-high) payment scheme. Specifically, we label a payment structure as flexible if there is at least 1 year of after tax pension benefits that has 10% higher or lower payments than previous year, taking first pillar pension benefits into account. Examples of a flat annuity include retirement at the statutory retirement age (default), or early retirement with bridging pension and flat payment afterwards. Examples of a flexible annuity include early retirement with bridging pension and high-low payments (starting at any point during retirement), or retirement at the statutory retirement age with high-low or low-high payments (starting at any point during retirement).[16]

Why are we specifically interested in flat and flexible payments in combination with time and risk preferences? Firstly, for given CRRA curvature, we hypothesize that a present-biased (future-biased) individual prefers flexible payments, because it has the opportunity to frontload (backload) pension benefits with high-low (low-high) payments and, therefore, fulfill his preferences. On the other hand, we hypothesize that a patient individual, with β and δ both close to 1, prefers flat payments. Secondly, for given (present-biased) time preferences, we hypothesize that an individual with a near linear CRRA utility function (curvature close to 1) prefers flat payments over flexible payment to smooth consumption throughout time. So, time and risk preferences are two plausible channels for the annuitization decision, but such preferences

[15]The legal condition states the higher payments versus the lower payments cannot exceed the ratio 100:75, such that the lower benefits at least equal 75% of the higher benefits.

[16]Pension benefits can legally be increased or decreased until the age of 78.

remain frequently unobserved in studying actual decision making.

A. Predicting behavior

We study how well risk and (present-biased) time preferences explain individual annuitization decisions, by using a life-cycle expected utility model that includes the individually estimated preferences. We follow 3 steps. Firstly, we compute the utility value of the actual (observed) real-life annuitization decision at retirement. Secondly, we compute the utility value of the annuity that has *not* been chosen; this is so to say the foregone alternative. For example, if an individual chose a flat annuity, then the foregone alternative was a flexible annuity. Finally, we compare whether the actual or alternative annuity yields the highest utility. If the actual chosen annuity indeed yields higher utility than the foregone alternative annuity, then the individual made a 'correct' choice. Correct meaning in line with his risk and (present-biased) time preferences, in combination with the life-cycle expected utility model. If the actual chosen annuity yields lower utility than the foregone alternative annuity, then the individual made a choice *not* in line with his preferences.

To determine the payment scheme of the (unobserved) foregone alternative, we proceed as follows. To start, we compute the individual's pension wealth by the present value of all future payments of the actual chosen annuity. In line with the fund's present value calculations, we use (i) fund specific survival probabilities for every date, cohort and gender, and (ii) an actuarial interest of 1.39% to discount future payments, as set by the Dutch Central Bank in 2018 based on the yield curve. Consequently, we convert the individual's pension wealth into the (unobserved) foregone alternative. If the retiree actually chose a flexible annuity, then we convert the pension wealth into a (default) flat annuity which starts at the chosen date of retirement. For example, in case of early retirement, we let the retiree still retire early, but he receives flat payment rather than high-low payments. If the retiree actually chose a flat annuity, then we convert the pension wealth into a flexible high-low annuity starting at the chosen date of retirement.[17] Based on the average fund's high-low choices, we set the duration of the high payments to 6 years with the lower benefits equaling (the legally maximum allowed) 75% of the higher benefits.

The life-cycle expected utility model determines the annuity's utility value based on the individually estimated risk and (present-biased) time preferences. The life-cycle model computes non-linear expected CRRA utility (3) at retirement date $t = 0$ for all future after tax annuity payments x_t, $t = 0, ..., T$ with T the time of death. The model includes fund specific survival probabilities $p^i_{x,t}$ at each time t for age x with i male or female. Mathematically, life-cycle expected utility at retirement is given by

$$\mathbb{E}[U] = \sum_{t=0}^{T} p(t)\phi(t; \hat{\beta}, \hat{\delta})U(x_t; \hat{\alpha}), \tag{10}$$

where $\phi(t; \hat{\beta}, \hat{\delta})$ is the (individually estimated) discount structure at time t. The quasi-hyperbolic discounting model requires a distinction between the present and the future. In line with the duration of the average observed high payments, we set the present-bias interval equal to $\tau = 6$, such that after 6 years individuals value consumption lower with the additional present-bias factor β.

Table 5, Quasi-hyperbolic model, shows the *actual* observed annuity and the *expected* unobserved foregone annuity choices. We distinguish 4 groups: (actual flat, expected flat), (actual flat, expected flex), (actual flex, expected flex) and (actual flex, expected flat). Out of the $N = 405$ retirees, 255 retirees chose a flat annuity, while 150 retirees chose a flexible annuity. The number of retirees choosing the flat annuity is possibly higher, because it is the default option. According to the individuals' preferences in the life-cycle expected utility model, we would expect that 181 retirees choose a flat annuity and that 224 retirees choose a flexible annuity. More specifically, 102 retirees chose a

[17]Another option would have been to start the high-low payments somewhere before the age of 78, or to convert the pension wealth into a flexible low-high annuity. However, in our sample most retirees that choose a flexible annuity do so by a high-low structure starting immediately at (possibly early) retirement age.

flat annuity and 71 retirees chose a flex annuity, as expected according to their preferences. On the other hand, we observe that 153 (79) retirees chose a flat (flexible) annuity, while a flexible (flat) annuity suits better according to their preferences in terms of expected utility.

On an aggregate level, 18% of the retirees did not choose according to their preferences in the expected life-cycle model.[18] So, how useful is our life-cycle model? Using a χ^2-test, we test the null-hypothesis H_0 that the actual observed annuity choices are independent from the expected utility choices. We find a p-value < 0.01, such that we reject H_0 at the 1% significance level and above. This is some first suggestive evidence that individually estimated preferences have the potential to explain actual annuity decisions.

Rather than having only a 'correct' or 'wrong' prediction, we are interested by how much risk and (present-biased) time preferences explain actual financial decision making. To this end, we compute prediction errors that indicate the magnitude of the difference between the actual (act) and expected (exp) annuity choices. The prediction error ε is defined as the annual missed certainty equivalent consumption due to the actual annuity decision (since the expected annuity decision always yields the highest utility by definition):

$$\sum_{t=0}^{T} p(t)\phi(t;\hat{\beta},\hat{\delta})U(x_t^{act};\hat{\alpha}) = \sum_{t=0}^{T} p(t)\phi(t;\hat{\beta},\hat{\delta})U(x_t^{exp}\cdot(1+\varepsilon);\hat{\alpha}). \tag{11}$$

If the prediction error is zero, then our expected utility model with individual preferences explains the actual choice of the retiree entirely successful. In Table 5, this holds for the 102 retirees in the northwest quadrant (actual flat, expected flat) and for the 71 retirees in the southeast quadrant (actual flex, expected flex). However, if the prediction error ε is < 0, then individual preferences only partially explain the actual choice of the retiree and the severity of misprediction is given by the magnitude of ε in terms of annual certainty equivalent consumption. In Table 5, the model mispredicts for 79 retirees in

[18] Table 5, Quasi-hyperbolic model, shows that 153-79=74 of the 405 retirees are expected to switch from flat to flexible (or vice versa) when comparing actual choices with expected utility choices.

the group (actual flex, expected flat) and for 153 retirees in the group (actual flat, expected flex).

Figure ?? shows the distribution of the prediction errors for all retirees in the upper panel. Prediction errors cluster mainly around zero or close to zero, which supports our hypothesis that risk and (present-biased) time preferences explain financial decision making. Table 6 presents the distribution in more detail. For 83.21% of the retirees the prediction error is equal to or larger than -5%. Equivalently, for 83.21% of the retirees our model makes a prediction such that the annual certainty equivalent consumption loss is only 5% or lower. For 17% of the retirees the prediction error is more severe and equals an annual certainty equivalent consumption loss above 5%. In other words, given an error margin ε of 5% (2%), risk and (present-biased) time preferences explain for more than 83% (67%) of the retirees actual annuitization decisions. In case we only allow perfect predictions, $\varepsilon = 0$, risk and (present-biased) time preferences explain for nearly 43% of the retirees the actual annuitization decisions, which is in line with the number of retirees in the groups (actual flat, expected flat) and (actual flex, expected flex) from Table 5.

The bottom panel in Figure ?? shows the distribution of prediction errors where the model only mispredicts ($\varepsilon \neq 0, \varepsilon < 0$), i.e. the groups (actual flat, expected flex) and (actual flex, expected flat). The group of 153 retirees (actual flat, expected flex) is larger than the group of 79 retirees (actual flex, expected flat). Thus, the group that chose the flat annuity while, according to their preferences, a flexible annuity yields higher expected utility is larger than the group that chose the flexible annuity while, according to their preferences, a flat annuity yields higher expected utility.

However, the mean (median) prediction error in the group (actual flat, expected flex) equals -3.48% (-2.65%), while in the group (actual flex, expected flat) the mean (median) equals -6.25% (-3.16%). So, prediction errors stem mainly from mispredictions in the group (actual flex, expected flat) and the variation of prediction errors is larger as well. 20 individuals, out of $N = 405$, have a prediction error that is strictly smaller than -10%. These individuals have some rather interesting preferences: future bias ($\hat{\beta} > 1$) with strong long-term impatience ($\hat{\delta} < 0.7$) and convex utility curvature. We suspect that due to the future bias, an actual annuity based on a high-low payment scheme does not fit such preferences very well and, therefore, we observe a prediction error of -10% or smaller.

In conclusion, risk and (present-biased) time preferences explain real-life annuitization decisions up to 83.21% for an error margin of 5% annual missed consumption. For more than 43% of the retirees individually estimated preferences explain precisely ($\varepsilon = 0$) actual annuity choices. Prediction errors lie on average in the range of -3.48% to -6.25% missed annual certainty equivalent consumption, where the errors are mainly driven by the subgroup of retirees (actual flex, expected flat).

B. Welfare effects

Given that risk and (present-biased) time preferences predict financial decision making to a large extent, in this final section we can address the welfare effects of freedom of choice. Freedom of choice, by means of the option to take a flexible annuity, creates potential and realized welfare gains, or losses. We explicitly compute the potential and realized welfare effects of freedom of choice in annuitization decisions, and we discuss whether a paternalistic policy may be welfare improving (aimed at addressing present-biased behavior). Much of the paternalism reflected in the modern welfare state is an effort to influence intertemporal choices (Ericson and Laibson, 2019).

To evaluate a policy, such as freedom of choice in annuitization decisions, a welfare criterion is needed. A common choice is to evaluate welfare from the long-run perspective, setting $\beta = 1$, on the grounds that these are the preferences that are persistent (Ericson and Laibson, 2019). Thus, for each individual we set $\hat{\beta} = 1$ and we repeat our previous analysis. Using the life-cycle expected utility model in equation (10) we compute the *optimal* annuity's utility value. Optimal in the sense of long-run persistent preferences without being subject to present bias.

Table 5, Welfare model, shows the *actual* observed annuity choice and the *optimal* annuity choice from a persistent welfare perspective. Of course, the actual observed annuity choices are identical to the Quasi-hyperbolic model: 255 retirees chose flat, 150 retirees chose flexible. However, according to the long-run individual's preferences without present bias ($\hat{\beta} = 1$), we expect that it is optimal for 200 retirees to choose a flat annuity and for 205 retirees to choose a flexible annuity. Compared to the Quasi-hyperbolic model, the expected utility model now predicts that a higher number of retirees should choose a flat annuity (from 181 to 200), while a lower number of retirees should prefer a flexible annuity. This is intuitive, because *not* being subject to present bias pulls individuals away from the tempting choice of a high-low scheme. Compared with actual choice behavior, we still observe that too many (few) individuals chose a flat (flexible) annuity according to our welfare-expected utility model. A potential reason might be the paternalistic default of a flat annuity at retirement.

Table 7 indicates the signs of the welfare implications together with individual present-bias and time-preference estimates. We distinguish between potential and realized welfare effects, and we split the effects in gains (+), losses (-) and no effect (0). Either preferences are in line with actual choice behavior — (actual flat, expected flat) and (actual flex, expected flex) — or preferences dot not match up with actual choice behavior — (actual flat, expected flex) and (actual flex, expected flat). We are interested in the welfare effects of freedom of choice, by means of the option to take a flexible annuity. Thus, the possibility (actual flat, expected flat) has no effect on the welfare analysis, or on policy making, and as such we do not display it.

The table clearly shows that retirees who actually chose a flexible annuity are more subject to present bias (i.e. lower present-bias factors $\hat{\beta}$) than retirees who actually chose a flat annuity. This observation is in line with the intuition that present-biased retirees are tempted to choose a high-low payment scheme. The difference between both groups in mean and median estimated present-bias factors equals approximately 7%. A Mann-Whitney ranksum test between the groups 'actual flat' (1.) and 'actual flex' (2. + 3.) shows that the difference in estimated present-bias factors is statistically significant at the 1% level.

Potential welfare gains (+) are given by the individuals that should choose in expectation a flexible annuity according to our welfare-expected utility model. Namely, from a long-run welfare perspective ($\hat{\beta} = 1$), it increases the expected utility of these retirees to choose a flexible annuity and, therefore, welfare increases. Hence, potential welfare gains of freedom of choice stem from the options (actual flat, expected flex) and (actual flex, expected flex). As the table confirms, indeed the average long-run discount factors are the lowest among these 2 groups (0.88 and 0.94), which shows that these retirees are the most impatient in the long run and prefer high-low schemes. Mann-Whitney ranksum tests between all groups (1., 2.), (1., 2.) and (2., 3.) show that the differences in estimated long-run discount factors are statistically significant at the 1% and 5% levels.

However, *realized* welfare effects of freedom of choice are given by the individuals that actually chose a flexible annuity at retirement. Individuals in the option (actual flex, expected flex) chose the flexible annuity in line with their preferences. On average, they suffer the most from present bias and have a quite low discount rate, especially compared to group 3. As such, the flexible annuity leads to realized welfare gains for this group 2. However, individuals in the category (actual flex, expected flat) chose a flexible annuity while according to their long-run preferences ($\hat{\beta} = 1$) it would have been optimal to choose a flat annuity, such that the flexible annuity creates realized welfare losses for this group 3 (they would be better off sticking to the default). The key mechanism is the average low present-bias factor of this group that tempts them to choose a flexible annuity, while in the long-run they show patient behavior since their average long-run discount factor is very close to 1.

Welfare distribution and correlations

Rather than only indicating the sign of the welfare effect, we are interested in the magnitude of welfare gains and losses and, secondly, whether the welfare effects depend on characteristics such as education and income. We quantify the welfare gains and losses according to equation (11) from the persistent welfare perspective with $\hat{\beta} = 1$.

For the group (actual flat, expected flex), ε is the potential annual certainty equivalent consumption that yields welfare gains through the flexible annuity. For the group (actual flex, expected flex), we compute the potential and realized welfare gains as follows. We counterfactually assume as if this group actually chose a flat annuity, such that we can quantify the potential and realized certainty equivalent consumption gain ε of introducing a flexible annuity. For the group (actual flex, expected flat), we directly compute ε as in equation (11). ε is negative and indicates the realized welfare losses through the flexible annuity option, in terms of missed annual certainty consumption.

Figure **??** shows the distribution of welfare losses and gains. The welfare effects appear to be quite symmetric, but the center of the distribution lies approximately at 4%. This indicates that on average we can expect welfare gains due to freedom of choice by means of a flexible annuity option. Remember from our predictive analysis that risk and (present-biased) time preferences were not always successful in explaining actual choice behavior. For an error margin of 5%, preferences explain for nearly 84% of the sample actual annuitization decisions.

Table 8 shows a detailed analysis of the welfare distribution for several prediction error margins. For an error margin of 5%, we find that the mean (median) potential welfare effect is positive and leads to annual gains of 3.00% (2.01%). On average, this leads to a potential monetary welfare gain of €13,607 in terms of present value pension wealth at retirement. The realized welfare effect, as shown in Panel B, is only 0.62% or €2,762, which is still positive but substantially smaller than the potential welfare gain. More specifically, the 5%-percentile shows that realized welfare is even negative. Hence, a key takeaway is that policy making can be improved to guide individuals in annuitization decisions, because there is an additional welfare gain possible of 2.38% (€10,845). Effects are similar for smaller prediction error intervals. In general, we conclude that potential welfare gains are possible due to freedom of choice, but realized welfare is substantially lower and can even be negative in some cases.

Finally, we are interested whether welfare gains and losses cluster at particular groups of individuals. Figure 7 shows the bivariate relations between the welfare effects, and education and income. Additionally, we indicate the fraction of participants who fall in a particular education or income category. A positive value on the vertical axis indicates welfare gains, while a negative value indicates welfare losses.

The left panel shows that there is a strong relation between education and welfare effects. On average, lower educated individuals are subject to welfare losses, while higher educated individuals tend to profit from freedom of choice in terms of welfare gains. The other moments of the distribution yields similar conclusions. Recall that education correlates negatively with the present-bias factor. Thus, a potential mechanism might be that lower educated individuals are tempted to choose a flexible annuity because of present bias, while a flat annuity yields higher expected utility according to their long-run persistent preferences. Our finding is in line with the observation of Merkle et al. (2017), who report that present-biased individuals are tempted to deplete their pension wealth faster than time-consistent individuals. The relation between welfare and education is statistically significant at a 10% level using a Spearman's rank correlation test.

The right panel shows an even stronger relation, namely between income and welfare. The very low and very high income categories (although containing few observations) are subject to low or negative welfare effects, compared to the other income categories who experience welfare gains. The U-shaped pattern is confirmed by the mean, median and 25%-percentile of the distribution. The relation is significant at any reasonable significance level.[19]

Conclusion

In this paper, we analyze 3 research questions. First of all, we jointly estimate risk and (present-biased) time preferences in a real-life context, with long

[19] We also tested for relations between welfare and gender, partner, life expectanct, private savings, homeownership and mortgage, but we did not find any relationship worth mentioning.

horizons, for a large group of pension fund participants. We base our method on the Convex Time Budgets of Andreoni and Sprenger (2012a) with an additional present-bias task from the INTRA study, conducted by the University of Zurich. Secondly, we correlate the estimated preferences with personal characteristics and we use a structural life-cycle model, based on the estimated preferences, to predict real-life financial decision making in the context of annuitization decisions. Thirdly, we quantify the welfare effects of freedom of choice in financial decision making and we study where welfare gains cluster in the population. To our knowledge, we are the first to relate jointly estimated risk and (present-biased) time preferences to actual financial decision making by means of a (non-linear) life-cycle model.

On average, pension fund participants show present-biased behavior, like most human beings and animals (Frederick et al., 2002). Retirees are less present biased than active participants. In the context of pension decision making, involving long horizons and large stakes, we find highly plausible annual discount rates close to 4%. The flexible annuity from the Dutch pension fund, replicating many characteristics of a lumpsum, has been chosen more by present-biased individuals than patient individuals. More generally, risk and (present-biased) time preferences explain for more than 83% of the retirees actual annuitization decisions. Realized welfare gains of the flexible annuity are lower than its potential welfare gains. Especially high educated and high income groups profit from freedom of choice by means of a flexible annuity in the payout phase.

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Tables

Table 1: **Overview experimental design.** Choice sets in the Convex Time Budgets and present-bias task. t and k are in years, and a_t and a_{t+k} are in Euros. Annual r is the yearly interest rate in percent (unadjusted for risk) and calculated as $((1+r)^{1/k}-1)\times 100$. Subjects enter an amount (in €) for c_1.

Task	Scenario	Set	t	k	p_{t+k}	c_t	c_{t+k}	$1+r$	Annual r
Convex Time Budgets	1	1	1	10	0.5	10,000	14,100	1.41	3.50
	2	1	1	10	0.5	10,000	14,900	1.49	4.07
	3	1	1	10	0.5	10,000	16,600	1.66	5.20
	4	1	1	10	0.5	10,000	19,300	1.93	6.80
	5	1	1	10	0.5	10,000	22,400	2.24	8.40
	6	2	1	10	0.7	10,000	12,000	1.20	1.84
	7	2	1	10	0.7	10,000	12,600	1.26	2.34
	8	2	1	10	0.7	10,000	14,000	1.40	3.42
	9	2	1	10	0.7	10,000	16,300	1.63	5.01
	10	2	1	10	0.7	10,000	19,000	1.90	6.63
	11	3	1	10	0.9	10,000	10,500	1.05	0.49
	12	3	1	10	0.9	10,000	11,100	1.11	1.05
	13	3	1	10	0.9	10,000	12,300	1.23	2.09
	14	3	1	10	0.9	10,000	14,400	1.44	3.71
	15	3	1	10	0.9	10,000	16,700	1.67	5.26
	16	4	1	10	1.0	10,000	10,000	1.00	0.00
	17	4	1	10	1.0	10,000	10,500	1.05	0.49
	18	4	1	10	1.0	10,000	11,700	1.17	1.58
	19	4	1	10	1.0	10,000	13,600	1.36	3.12
	20	4	1	10	1.0	10,000	15,900	1.59	4.75
Present bias	21	5	0	1	1.0	800	c_1	-	-

Table 2: **Sample characteristics, comparison with pension fund.** Active participants are participants that actively accrue pension rights at the pension fund. Standard deviation between parentheses.

Panel A: Active participants and retirees				
		Pension fund	Sample mean	N
Male		0.567	0.568	1110
			(0.496)	
Retired		0.384	0.365	1110
			(0.482)	
Panel B: Retirees				
		Pension fund	Sample median	N
Age	Male	67.31	67.07	270
			(1.83)	
	Female	67.14	66.83	135
			(2.43)	
	Total	67.24	67.02	405
			(2.06)	
Income	Male	22,670	28,069	246
			(16,495)	
	Female	16,637	16,418	121
			(12,221)	
	Total	20,102	23,047	367
			(16,032)	

Table 3: **Individual present bias, annual discounting and curvature parameter estimates.** Two-limit Tobit maximum likelihood and Ordinary Least Squares (OLS) estimates for CRRA utility x^α/α and background income zero. Standard errors are calculated as $\sigma/\sqrt{N}$, where σ is the standard deviation.

	Median	Mean	Standard Deviation	Standard Error	25th Percentile	75th Percentile	Min	Max	N
Tobit: All									
Present bias $\hat{\beta}$	0.878	0.868	0.237	0.007	0.719	0.989	0.473	1.488	1110
Discount factor $\hat{\delta}$	0.962	0.967	0.172	0.005	0.921	1.016	0.505	1.443	1110
CRRA curvature $\hat{\alpha}$	0.966	0.938	0.132	0.004	0.910	0.985	0.559	1.210	1110
Tobit: Actives									
Present bias $\hat{\beta}$	0.855	0.850	0.235	0.009	0.696	0.981	0.473	1.488	705
Discount factor $\hat{\delta}$	0.963	0.970	0.168	0.006	0.922	1.017	0.505	1.443	705
CRRA curvature $\hat{\alpha}$	0.966	0.943	0.127	0.005	0.912	0.985	0.559	1.210	705
Tobit: Retirees									
Present bias $\hat{\beta}$	0.911	0.899	0.237	0.012	0.776	1.005	0.473	1.488	405
Discount factor $\hat{\delta}$	0.962	0.963	0.180	0.009	0.917	1.014	0.505	1.443	405
CRRA curvature $\hat{\alpha}$	0.966	0.930	0.140	0.007	0.906	0.984	0.559	1.210	405
OLS: All									
Present bias $\hat{\beta}$	0.868	0.838	0.183	0.005	0.716	0.971	0.482	1.135	1110
Discount factor $\hat{\delta}$	0.970	0.982	0.105	0.003	0.929	1.023	0.766	1.253	1110
CRRA curvature $\hat{\alpha}$	0.940	0.920	0.175	0.005	0.879	0.963	0.435	1.351	1110

Table 4: **Multivariate relation between present bias and socio-economic characteristics**. The table presents correlations of three Ordinary Least Squares (OLS) regressions with the individually estimated present-bias factor $\hat{\beta}$ as dependent variable. Controls include the duration and reported complexity of the survey. ** and * indicate statistical significance at the 5% and 10% level, respectively. Robust standard errors (MacKinnon and White, 1985) between parentheses.

	(1)	(2)	(3)
Demographics			
Male	0.025		0.032*
	(0.015)		(0.019)
Age	0.004**		0.004**
	(0.001)		(0.002)
Low degree	0.006		-0.011
	(0.032)		(0.039)
Medium degree	0.029		0.014
	(0.029)		(0.036)
High degree	0.045		0.018
	(0.03)		(0.037)
Financial			
Income		0.001	0.001
		(0.003)	(0.004)
Savings 5k-10k		0.051	0.051
		(0.031)	(0.031)
Savings 10k-30k		0.06**	0.056**
		(0.026)	(0.026)
Savings 30k-50k		0.077**	0.064**
		(0.028)	(0.028)
Savings 50k+		0.094**	0.083**
		(0.027)	(0.027)
Controls			
Duration	0	0	0
	(0)	(0)	(0)
Difficulty: easy	0.024	0.029*	0.029*
	(0.015)	(0.016)	(0.016)
Difficulty: neutral	-0.001	-0.001	0
	(0.01)	(0.01)	(0.01)
Difficulty: difficult	-0.007	-0.008	-0.008
	(0.008)	(0.008)	(0.008)
Difficulty: very difficult	-0.019**	-0.025**	-0.024**
	(0.008)	(0.008)	(0.008)
Intercept	0.569**	0.809**	0.57**
	(0.082)	(0.037)	(0.102)
F-statistic	4.705	4.63	4.064
p-value	0	0	0
R^2	0.042	0.049	0.064
N	1072	903	902

Table 5: **Cross tables of actual choices against predicted choices.** The quasi-hyperbolic cross table shows the actual choices against the expected-utility choices according to the individually estimated risk and (present-biased) time preferences in the life-cycle model. The welfare cross table shows the actual choices against the expected choices according to the individually estimated risk and time preferences under quasi-hyperbolic discounting, but with constraint $\hat{\beta}_i = 1$ for each retiree i.

Quasi-hyperbolic model

		Actual		
		Flat	Flex	Total
Expected	Flat	102	79	181
	Flex	153	71	224
	Total	255	150	405

Welfare model

		Actual		
		Flat	Flex	Total
Optimal	Flat	115	85	200
	Flex	140	65	205
	Total	255	150	405

Table 6: **Distribution of prediction errors ε.** The number of retirees in the analysis equals $N = 405$.

	Prediction error ε interval (%)						
	0	[-1, 0)	[-2, -1)	[-3, -2)	[-4, -3)	[-5, -4)	$(-\infty$, -5)
Fraction	42.72%	12.84%	11.60%	5.43%	6.67%	3.95%	16.79%
Cumulative	42.72%	55.56%	67.16%	72.59%	79.26%	83.21%	100.00%

Table 7: **Potential and realized welfare effects with present bias and time preference estimates.** This table presents the potential and realized welfare gains and losses, together with the average estimated present-bias factor and long-run discount factor ($N = 290$ retirees)

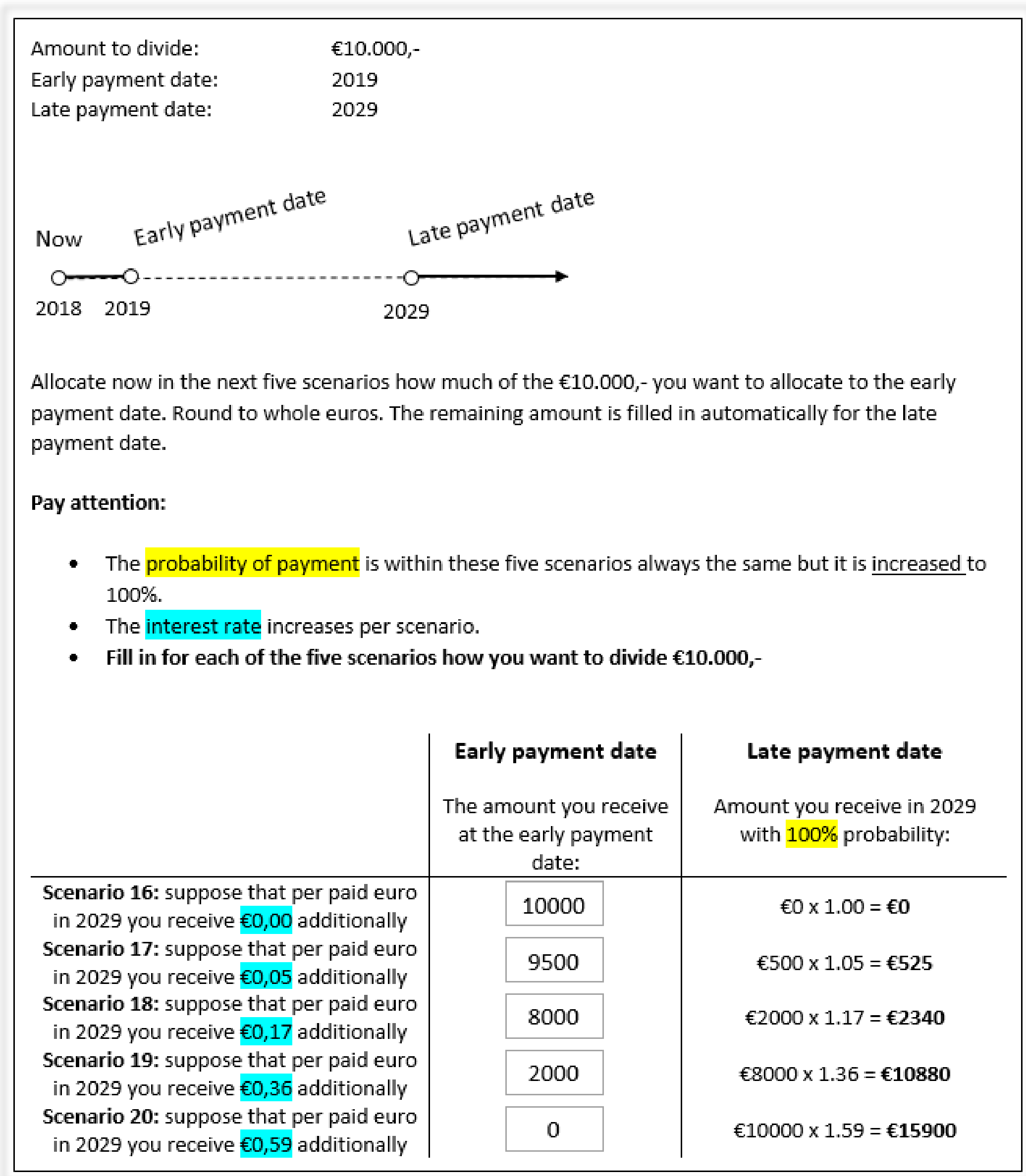
	Potential	Realized	mean($\hat{\beta}$)	mean($\hat{\delta}$)
1. Actual **flat**, expected **flex**	+	0	0.97	0.88
2. Actual **flex**, expected **flex**	+	+	0.90	0.94
3. Actual **flex**, expected **flat**	0	-	0.91	0.98

Table 8: **Potential and realized welfare gains and losses due to freedom of choice.** This table presents the certainty equivalent (CE) consumption and monetary welfare effects (in €) for several prediction error intervals.

	Prediction error ε interval (%)											
	0		[-1, 0]		[-2, 0]		[-3, 0]		[-4, 0]		[-5, 0]	
	CE	€	CE	€	CE	€	CE	€	CE	€	CE	€
Panel A: Potential welfare												
Mean	4.79	21,750	3.73	16,721	2.99	13,433	2.90	13,046	2.91	13,067	3.00	13,607
Median	2.53	10,145	1.98	7,496	1.75	6,184	1.76	6,549	1.85	7,366	2.01	8,003
Std. Dev.	6.01	28,738	4.70	22,476	3.57	17,545	3.30	16,362	3.12	15,465	3.13	15,802
5% perc.	0.31	1,511	0.27	1,257	1.00	6,028	1.44	9,631	2.24	11,749	2.68	15,264
95% perc.	16.62	85,329	12.89	65,862	9.21	46,716	8.07	40,857	6.99	35,235	6.59	33,159
Panel B: Realized welfare												
Mean	1.70	7,727	1.25	5,650	0.98	4,438	0.86	3,842	0.73	3,196	0.62	2,762
Median	0.89	3,581	0.64	2,394	0.47	1,691	0.42	1,396	0.35	1,160	0.24	916
Std. Dev.	2.17	10,354	1.76	8,459	1.52	7,241	1.45	7,093	1.40	6,905	1.40	6,839
5% perc.	0.07	405	-0.16	-864	-0.29	-1,297	-0.35	-2,514	-0.59	-3,923	-0.76	-4,241
95% perc.	5.96	30,578	4.67	23,946	3.90	19,973	3.61	18,466	3.30	16,900	3.14	16,090

Figures

Figure 1: **Decision screen.** In each scenario the subject allocates $m = €10.000$ between the early payment date $t = 1$ year (2019) and the late payment date with delay $k = 10$ years (2029). In this set, the late payment is with a probability p_{t+k} of 100%. The gross interest rate $1 + r$ over k years in the 5 scenario varies from 1.00 to 1.59. .



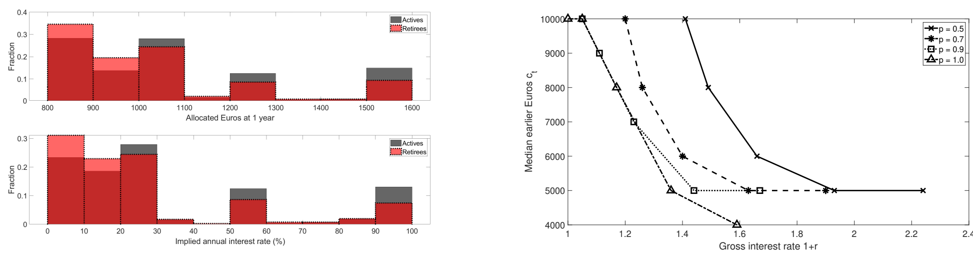
Amount to divide:	€10.000,-
Early payment date:	2019
Late payment date:	2029

Allocate now in the next five scenarios how much of the €10.000,- you want to allocate to the early payment date. Round to whole euros. The remaining amount is filled in automatically for the late payment date.

Pay attention:

- The probability of payment is within these five scenarios always the same but it is increased to 100%.
- The interest rate increases per scenario.
- **Fill in for each of the five scenarios how you want to divide €10.000,-**

	Early payment date The amount you receive at the early payment date:	**Late payment date** Amount you receive in 2029 with 100% probability:
Scenario 16: suppose that per paid euro in 2029 you receive €0,00 additionally	10000	€0 x 1.00 = **€0**
Scenario 17: suppose that per paid euro in 2029 you receive €0,05 additionally	9500	€500 x 1.05 = **€525**
Scenario 18: suppose that per paid euro in 2029 you receive €0,17 additionally	8000	€2000 x 1.17 = **€2340**
Scenario 19: suppose that per paid euro in 2029 you receive €0,36 additionally	2000	€8000 x 1.36 = **€10880**
Scenario 20: suppose that per paid euro in 2029 you receive €0,59 additionally	0	€10000 x 1.59 = **€15900**



(a) **Present-bias task.** (b) **Convex Time Budgets**

Figure 2: **Choice behavior.** (a) Distribution of allocated Euros c_1 in the present-bias task, together with the implied annual interest rate. Responses are winsorised at the 5% level. Implied annual interest rate calculated as $(c_1/800 - 1) \times 100$. (b) Median allocated Euros at early payment a_t against the gross interest rate $1 + r$ per payout probability p in the Convex Time Budgets.

Figure 3: **Estimated distribution of individual present bias, annual discounting and curvature parameters.** Responses are winsorised at the 5% level.

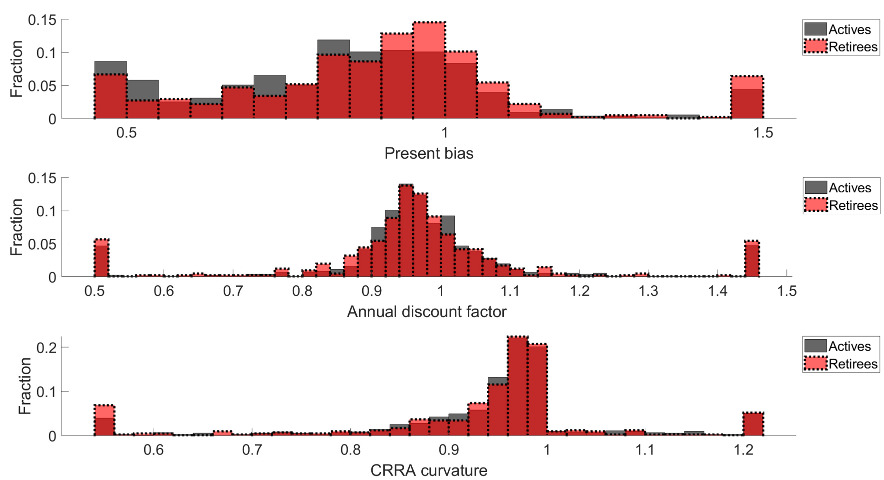


Figure 4: **Bivariate relation between present bias and demographic variables.**

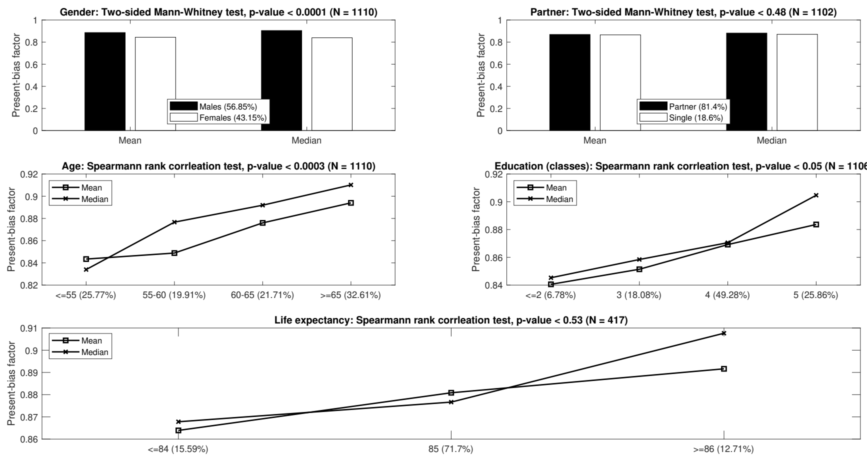
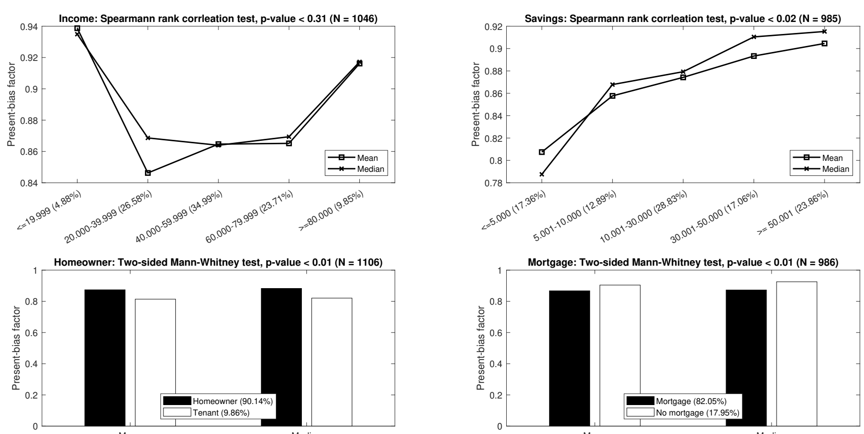
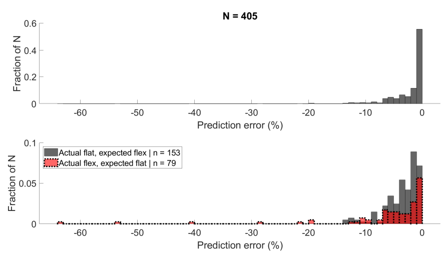
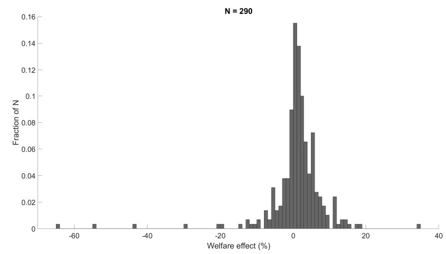


Figure 5: **Bivariate relation between present bias and financial variables.**





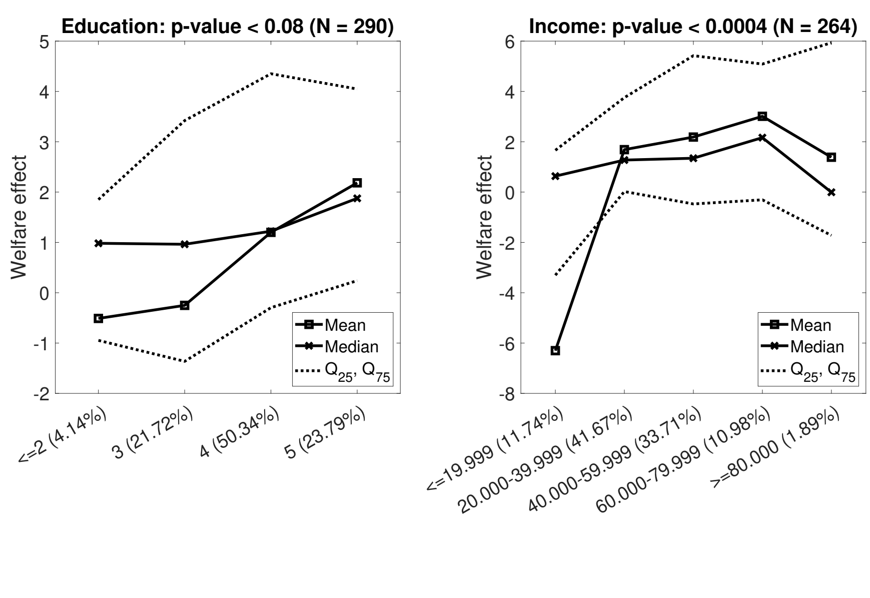
(a) **Prediction errors.**



(b) **Welfare effects.**

Figure 6: **Distributions of prediction errors ε, and welfare losses and gains.** (a) The upper panel shows the distribution of prediction errors for the whole sample (including correct predictions), while the bottom panel shows the distribution of prediction errors for mispredictions only (excluding correct predictions). (b) Distribution of welfare losses and gains due to freedom of choice.

Figure 7: **Bivariate relation between welfare effects, and education and income.**



Online Appendices

For Online Publication

A Individual parameter estimation

There are N experimental subjects and P convex budget decisions, where we substitute the present-bias task in the CTB decision. We assume that each subject j makes her allocation decision $c_{t_{i,j}}$, $i = 1, ..., P$, according to the relationship in (6), but that each decision is made with some additive mean-zero (potentially correlated) error. That is,

$$\ln\left(\frac{c_t + w_1}{c_{t+k} + w_2}\right)_{i,j} = \left(\left(\frac{\ln\beta}{\alpha-1}\right) + \left(\frac{\ln\delta}{\alpha-1}\right)\cdot k_i\right)\cdot \mathbb{1}_{p_{t+k_i}=1} + \left(\frac{1}{\alpha-1}\right)\cdot\left(\ln(1+r_i) + \ln(p_{t+k_i})\right) + \varepsilon_{i,j}. \quad (12)$$

Stacking the P observations per individual j, we have

$$\ln\left(\frac{\boldsymbol{c_t} + \boldsymbol{w_1}}{\boldsymbol{c_{t+k}} + \boldsymbol{w_2}}\right)_{\boldsymbol{j}} = \left(\left(\frac{\ln\beta}{\alpha-1}\right) + \left(\frac{\ln\delta}{\alpha-1}\right)\cdot \boldsymbol{k}\right)\cdot \mathbb{1}_{\boldsymbol{p_{t+k}}=1} + \left(\frac{1}{\alpha-1}\right)\cdot\left(\ln(\boldsymbol{1}+\boldsymbol{r}) + \ln(\boldsymbol{p_{t+k}})\right) + \boldsymbol{\varepsilon_j}. \quad (13)$$

The vector $\boldsymbol{\varepsilon_j}$ is zero in expectation with variance-covariance matrix $\boldsymbol{\Sigma_j}$, a $P \times P$ matrix, allowing for arbitrary correlation in the errors $\varepsilon_{i,j}$. For each subject j, we assume that all decisions i are subject to an error with mean zero and variance σ_i^2. So, $\boldsymbol{\Sigma_j}$ is a (homogeneous) diagonal variance-covariance matrix with entries σ_i^2 on the diagonal and zeros off diagonal. In other words, the error term is the same within subject j for each decision i, but the error term may vary across individuals.

Equation (13) is easily estimated with ordinary least squares. However, the log-consumption ratio is censored by the corner responses on the budget constraint

$$\ln\left(\frac{\boldsymbol{c_t + w_1}}{\boldsymbol{c_{t+k} + w_2}}\right)_{\boldsymbol{j}} \in \left(\ln\left(\frac{\boldsymbol{0 + w_1}}{\boldsymbol{(m \cdot (1 + r)) + w_2}}\right)_{\boldsymbol{j}}, \ln\left(\frac{\boldsymbol{m + w_1}}{\boldsymbol{0 + w_2}}\right)_{\boldsymbol{j}}\right). \quad (14)$$

Namely, either the subject allocates the complete budget m to the late payment at gross interest rate $1+r$ (and allocates nothing to the early payment), or the subject allocates the complete budget m to the early payment (and allocates nothing to the late payment). These corner solutions motivate the use of censored regression techniques such as the two-limit Tobit model.

Finally, the risk- and time-preference parameters for each individual j can be estimated via the regression

$$\ln\left(\frac{\boldsymbol{c_t + w_1}}{\boldsymbol{c_{t+k} + w_2}}\right)_{\boldsymbol{j}} = \eta_{j,0} \cdot \mathbb{1}_{\boldsymbol{p_{t+k}}=1} + \eta_{j,1} \cdot (\ln(\boldsymbol{1 + r}) + \ln(\boldsymbol{p_{t+k}})) + \boldsymbol{\varepsilon_j}, \quad (15)$$

where $\eta_{j,0}$ and $\eta_{j,1}$ are the individual specific intercept and regression coefficient, respectively. For each individual j, the preference estimates for curvature, discounting and present bias are found via the non-linear combinations

$$\begin{aligned} \hat{\alpha} &= \frac{1}{\hat{\eta_{j,1}}}, \\ \hat{\delta} &= \exp\left[\frac{\hat{\alpha} - 1}{k - 1}\left(\hat{\eta}_0 - \frac{\hat{\alpha}}{\hat{\alpha} - 1} \ln\left(\frac{800 + w_0}{c_1 + w_1}\right)\right)\right], \\ \hat{\beta} &= \frac{1}{\hat{\delta}}\left(\frac{800 + w_0}{c_1 + w_1}\right)^{\hat{\alpha}}. \end{aligned} \quad (16)$$

A point of attention is that the background consumption parameters are known or fixed and, secondly, that the consumption ratio $(c_t + w_t)/(c_{t+k} + w_{t+k})$ is strictly positive, such that the log transform is well-defined. Similar to Andreoni and Sprenger (2012a), Andersen et al. (2014), and Potters et al. (2016), we restrict ourselves to the absence of background consumption.[20] The strength is that corner solutions are easily addressed by censoring models such

[20] We do a robustness check in Table 13 Online Appendix B with individual annual income as proxy for background consumption.

as two-limit Tobit maximum likelihood regression.

B Data appendix

Table 9: **Median individual tax levels in The Netherlands for active participants and retirees.** The tax levels are based on individual annual before tax income. We constructed the tax levels for actives by adding 10 percentage points to the tax level of the corresponding retiree income level.

	Tax (fraction income)	
Income (€)	Active participants	Retirees
<17,802	0.19676	0.09676
<20,018	0.18671	0.08671
<21,849	0.20572	0.10572
<23,731	0.23090	0.13090
<26,327	0.24774	0.14774
<29,729	0.26721	0.16721
<34,250	0.28571	0.18571
<40,542	0.29940	0.19940
<51,792	0.35565	0.25565
<65,000	0.39650	0.29650
<80,000	0.42698	0.32698
≥80,000	0.48345	0.38345

Table 10: **Summary statistics of the data.**

	Mean	Median	Standard Deviation	N
Panel A: Demographics				
Male	0.57	1.00	0.50	1110
Age	60.67	61.05	5.87	1110
Education	3.90	4.00	0.97	1106
Retired	0.36	0.00	0.48	1110
Partner	0.81	1.00	0.39	1102
Children	1.83	2.00	1.23	1106
Panel B: Financial				
Income	57,138	55,554	20,545	1046
Private savings	50,995	20,000	87,328	985
Homeowner	0.90	1.00	0.30	1106
Rent price	737	671	280	78
House price	302,503	268,000	249,895	930
Mortgage	0.82	1.00	0.38	986
Expect inheritance	0.25	0.00	0.44	1022
Inheritance amount	87,771	37,500	112,055	231
Leave bequest	0.58	1.00	0.49	782
Bequest amount	154,412	150,000	148,523	357
Panel C: Pension				
Pension income	22,460	20,851	13,747	1046
Pension income max	28,972	28,203	15,291	1046
Other pension income	7,921	500	16,819	296
Individual pension income	50,000	30,000	41,569	22
Part-time pension	0.00	0.00	0.05	405
AOW bridge	0.42	0.00	0.49	405
Flexible pension	0.39	0.00	0.49	405
Transfer partner pension	0.25	0.00	0.43	405
Intended retirement age	-2.58	-3.00	2.21	627
Panel D: Other				
Life expectancy	84.08	85.00	4.24	417
Duration	318.78	19.83	1,751.67	1110
Complexity	2.87	3.00	1.00	1076

Table 11: **Definition of variables.** [a] Participants could easily access this information via a provided link directing to house price administration

Variable	Definition
	Panel A: Demographics
Male	Dummy; 1 = male; 0 = female
Age	Age in years (pension fund administration)
Education	Classes; 0 = primary school; 1 = secondary school; 2 = pre-vocational education and training (LBO); 3 = vocational education and training (MBO); 4 = university of applied sciences (HBO); 5 = university
Retired	Dummy; 1 = retired participant (retiree); 0 = active participant (worker)
Partner	Dummy; 1 = married, registered partnership or cohabitation; 0 = no partner
Children	Number of children
	Panel B: Financial
Income	Individual annual before tax income. For retirees, all employer-related second pillar pension benefits received from the pension fund including state pension benefits. For workers, salary corrected for part-time work.
Private savings	Self-reported total individual amount of voluntary liquid savings (e.g. a bank account and/or investments) in one of the classes: (0-5,000), (5,001-10,001),(10,001-30,000), (30,001-50,000), (50,001-100,000), (100,001-200,000), (200,001-400,000), (> 400,000). Excluding house and pension savings.
Homeowner	Dummy; 1 = House owner, 0 = rent a house
Plan to buy	Dummy; 1 = Rent a house, but planning to buy a house, 0 = rent a house, but not planning to buy a house
Rent price	Self-reported current rent price of house (on household level) for tenants (including service fees, excluding gas, water and electricity costs)
House price	Self-reported current house price (on household level) for homeowners; 0 = renting a house[a]
Mortgage	Dummy; 1 = currently one or more mortgage loans; 0 = currently no mortgage loans
Expect inheritance	Dummy; 1 = expect to receive an inheritance (money, real estate or other possessions) during remaining life cycle; 0 = no
Inheritance amount	Individual expected inherited amount in one of the classes: (< 25,000), (25,001-50,000), (50,001-100,000), (100,001-300,000), (300,001-500,000), (> 500,000)
Leave bequest	Dummy; 1 = wish to leave a bequest (savings, house or other possessions) when passing away; 0 = no
Bequest amount	Individual expected bequest amount in one the classes: (< 25,000), (25,001-50,000), (50,001-100,000), (100,001-300,000), (300,001-500,000), (> 500,000)

Table 12: **Definition of variables (continued).** Att. is abbreviation for attitude, and AOW is abbreviation for state pension. [a] Participants could easily access this information via a provided link directing to the pension government administration. [b] Participants were provided that per year of early retirement pension benefits decrease by 6%, and per year of later retirement pension benefits increase by 8%. [c] Participants were shown that the average life expectancy in The Netherlands equals approximately 85 years.

Variable	Definition
	Panel C: Pension
Pension income	Individual annual before tax second pillar accrued pension rights.
Pension income max	Projected individual annual before tax second pillar accrued pension rights.
Other pension income	Self-reported individual annual before tax second pillar pension benefits received from other pension funds (e.g. accrued in the past) in one of the classes: 0 = none, (< 1,000), (1,002-5,000), (5,001-10,000), (10,001-20,000), (20,001-30,000), (30,001-50,000), (50,001-100,000), (> 100,000)[a]
Individual pension income	Self-reported individual annual before tax pension benefits received from insurance companies or banks in one of the classes: 0 = none, (< 5000), (5,001-10,000), (10,001-30,000), (30,001-50,000), (50,001-100,000), (100,001-200,000), (> 200,000)
Part-time pension	Dummy; 1 = administrated part-time pesion; 0 = no part-time pension
AOW bridge	Dummy; 1 = administrated AOW bridge (second pillar financial compensation in case of early retirement); 0 = no AOW bridge
Flexible pension	Dummy; 1 = administrated flexible pension in the form of a high-low or loh-high annuity; 0 = no flexible pension
Transfer partner pension	Dummy; 1 = administrated transfer of partner pension to old age pension; 0 = no transfer of partner pension
Intended retirement age	Intended retirement year with respect to the statutory retirement age in one of the classes (negative values indicate early retirement, positive values indicate later retirement): (< -5), (-5), (-4), (-3), (-2), (-1), (1), (2), (3), (> 3).
Att. pension choices	Classes; 1 = strongly disagree with more freedom of pension choices, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree with more freedom of pension choices
Att. premium stop	Classes; 1 = strongly disagree with the choice premium stop, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree with the choice premium stop
Att. flexible pension age	Classes; 1 = strongly disagree with the choice of a flexible pension age, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree with the choice of a flexible pension age
Att. flexible pension benefits	Classes; 1 = strongly disagree with the choice a flexible pension benefits, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree with the choice a flexible pension benefits
	Panel D: Other
Life expectancy	Expected life expectancy in years reported in one of the classes: (< 75), (75-84), (85), (86-90), (> 90)[c]
Duration	Minutes between starting and ending the survey
Complexity	Classes; 1 = very easy survey, 2 = easy, 3 = neutral, 4 = difficult, 5 = very difficult survey

Table 13: **Individual present bias, annual discounting and risk aversion parameter estimates with background income.** Two-limit Tobit maximum likelihood estimates with background income $w_t = w_{t+k}$ equal to yearly individual after-tax income. The CRRA utility function we use is $x^{(1-\alpha)}/(1-\alpha)$ for $\alpha \neq 1$: $\alpha = 0$ denotes risk neutral behavior, $\alpha > 0$ denotes risk aversion and $\alpha < 0$ denotes risk seeking behavior. Standard errors are calculated as $\sigma/\sqrt{N}$, where σ is the standard deviation.

	Median	Mean	Standard Deviation	Standard Error	25th Percentile	75th Percentile	Min	Max	N
Present bias $\hat{\beta}$	1.052	1.089	0.177	0.005	1.005	1.102	0.850	1.687	1046
Discount factor $\hat{\delta}$	0.951	0.942	0.125	0.004	0.910	0.996	0.593	1.198	1046
CRRA risk aversion $\hat{\alpha}$	1.448	1.654	2.759	0.085	0.827	2.549	-5.435	8.095	1046