Do Lottery Payments Induce Savings Behavior? Evidence from the Lab*

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Abstract

This paper presents the results of a laboratory experiment designed to investigate whether the option of a Prize Linked Savings (PLS) product alters the likelihood that subjects choose to delay payment. By comparing PLS and standard savings products in a controlled way, we find strong evidence that a PLS payment option leads to greater rates of payment deferral than does a straightforward interest payment option of the same expected value. The appeal of the PLS option is strongest among men and self-reported lottery players. We use the results of our experiment to structurally estimate the parameters of the decision problem governing time preference, risk aversion, and probability weighting. We employ the parameter estimates in a series of policy simulations that compare the relative effectiveness of PLS products as compared to standard savings products.

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1 Introduction

There is now widespread recognition that individual decision-making with regard to savings behavior often deviates from the standard neoclassical model of a risk-averse consumer making decisions according to the tenets of expected utility theory.[1] In recent years, many policies have been suggested or implemented that make use of observed deviations from the standard neoclassical model to "nudge" consumers toward increased savings.[2] Notable examples include changes in default 401(k) settings such that employees are automatically enrolled in savings plans (cf, Madrian and Shea (2001)) and the "Save More Tomorrow" (SMarT) plan that has workers pre-commit to setting aside future wage increases in a savings account (Thaler and Benartzi, 2004). Chetty, Friedman, Leth-Petersen, Nielsen, and Olsen (2012) present evidence that the impact of targeted savings policies is larger if they affect passive choice versus active choice. The policy interest in this question is largely driven by the observation that many low- and moderate- income households do not have adequate savings. For example, Lusardi, Schneider, and Tufano (2011) find that nearly half of Americans would potentially have trouble coming up with $2,000 in 30 days. There is increasingly a recognition that current savings products do not appeal to many low- to moderate- income consumers, generating an interest in innovation in the savings product space.

Prize Linked Savings (PLS) accounts constitute an alternative policy innovation in the domain of savings behavior. The concept of a Prize Linked Savings account is to add a stochastic element to an otherwise standard account, such that depositors periodically receive a chance to win a specified (and potentially large) prize that is a function of deposit amounts. PLS products are new to the United States, but have existed in some form around the world for hundreds of years. Currently the policy movement on PLS is ahead of the research, moving under the assumption that the addition of lottery-like features to otherwise standard savings products will induce individuals to save more. In 2009 a set of credit unions in the state of Michigan introduced the "Save to Win" PLS program, in conjunction with D2D Fund, a policy group focused on savings innovations for lower-income consumers. This program is considered a great success because it has successfully attracted deposits. Driven by this observation, in 2013, the states of North Carolina and Washington adopted the Save to Win program. Legislative efforts in additional states and recently the federal government would expand the reach of PLS products in the United States. But, crucially, there has yet to be research establishing that these products induce additional savings, as opposed to simply crowding out existing forms of savings. Attempts at running PLS field experiments

[1] The descriptive validity of expected utility theory has been challenged by a large body of experimental literature (e.g. Starmer (2000) for a review).

[2] The use of this term in this context is due to Thaler and Sunstein (2008).

with credit unions have not been successful, and so in this paper we turn to the experimental laboratory to generate evidence on this important question.

The idea behind PLS products is to leverage the appeal of gambling to entice people to invest in savings products that offer a positive expected return.[3] The stochastic return could be in addition to some guaranteed interest payment or it could constitute the entire return. A PLS product is unlike a traditional lottery ticket in that the principal is returned to the investor. The random component of the return on savings can take the form of in-kind prizes – as is commonly offered by commercial banks in Latin America – or as a cash prize awarded to account holders as a part of a semi-regular drawing – as is the case with Britain's Premium Bonds. Prize Linked Savings accounts are presumed to appeal to individuals' appetite for lottery-like products, either because of risk-loving preferences or probability weighting in the decision function that leads individuals to overweight the likelihood of a gain.[4] Alternatively, a preference for skewness (Mitton and Vorkink, 2007) or an entertainment value of gambling (Conlisk, 1993) might increase the appeal of the PLS.

In this paper we describe the results of a laboratory experiment designed to investigate whether the option of a PLS-type product alters the likelihood that subjects choose to save (i.e., delay payment). We also use the observed choice behavior to jointly estimate risk, discount, and probability weighting parameters under certain modeling assumptions. The popularity of PLS products in the settings in which they have been offered is often cited by policy advocates as evidence that they would be effective at encouraging savings. By comparing PLS and standard savings products in a controlled way, we are able to test whether the offer of PLS generates more savings behavior than otherwise equivalent non-PLS savings products.[5]

[3]Kearney, Tufano, Guryan, and Hurst (2010) provide an overview of prize-linked savings (PLS) products, including discussions of the history of such products, potential legal barriers, and descriptive evidence from some recent product roll outs in the United States.

[4] Nonlinear probability weighting has been put forth as an explanation for several behavioral phenomena. For example, Barberis and Huang (2008) show that such biased decision makers have a preference for skewness of returns in stocks. Sydnor (2010) argues that the over-weighting of small probabilities of a loss explains the fact that decision makers over-insure their homes against modest-scale risks. Similarly, Barseghyan, Molinari, O'Donoghue, and Teitelbaum (Forthcoming) argue that probability distortions (i.e., overweighting of claim probabilities) play a key role in determining households' deductible choices and lead them to risk-averse behavior. Snowberg and Wolfers (2010) argue that probability misperceptions can explain the so-called "favorite-long shot bias" in pari-mutuel markets, although Ottaviani and Sørensen (2009, 2010) provide game theoretical models which are also capable of explaining this behavioral finding. Finally, Hu and Scott (2007) argue that longevity annuities may be more attractive to consumers than immediate annuities because they over-weight the small probability of living long enough to receive a large payment.

[5] Providing lottery rewards has been shown in other contexts to have a positive effect. Volpp, John, Troxel, Norton, Fassbender, and Loewenstein (2008a) ran an experiment in which lotteries were provided as a reward for taking one's required medication daily. They find that participants were significantly more likely to follow the prescribed dosage during the intervention period, but that behavior falls back to pre-intervention levels after the experiment. In a related paper, Volpp, John, Troxel, Norton, Fassbender, and

The first main contribution of this paper is to determine whether the offer of a PLS type product increases the rate at which subjects choose to defer payment (which we take as indicative of savings behavior) as compared to the the offer of a guaranteed interest payment. We establish this in a laboratory experiment run on 96 students in the University of Maryland Experimental Economics Laboratory during March 2012. We followed the well-established practice of using binary choices to elicit preferences paired with probabilistically determined payments. We find strong evidence that a lottery-like payout leads to greater rates of payment deferral as compared to a straightforward interest payment of the same expected value. In other words, subjects make choices such that they appear to be more patient when the option paid later is a risky gamble than when it is a sure thing.[6] The appeal of the PLS product appears to be greatest among men, self-reported lottery players, and, although the effect is somewhat weaker, those who report relatively low amounts in their existing bank accounts. Our experiment establishes that subjects defer payment for a stochastic return even if they find an equivalent certain payment too low to invest. Our paper is the first one making this foundational point based on controlled binary choice problems while jointly estimating parameters of a general model.

A few other papers have also considered the interaction between time and risk preferences. The most closely related is Atalay, Bakhtiar, Cheung, and Slonim (Forthcoming) who also describe the results of a portfolio-choice experiment designed to investigate the appeal of a PLS product over interest-only savings as well as lottery tickets. They show that the offer of PLS increases savings and reduces lottery expenditures.[7] Two other papers — Keren and Roelofsma (1995) and Ahlbrecht and Weber (1997a) — report similar results to us in that making the delayed payment risky appears to make subjects more patient, while Anderson and Stafford (2009) reports results suggesting that adding risk induces subjects to prefer the early payment.[8]

Loewenstein (2008b) run a randomized experiment to study the effectiveness of lottery incentives in weight-loss programs. They find that participants subject to lottery incentive treatments weighed significantly less after 16 weeks and, despite subsequent weight gains, continued to weigh significantly less after 7 months.

[6]See Epper and Fehr-Duda (2013) for a summary of evidence of such behavior in the literature, and a model unifying time discounting and risk taking by allowing for interactions between these two concepts.

[7]Although interesting and closely related, there are a number of important distinctions. Their design differs from ours in that they do not always fix the expected return of the PLS product to be the same as the interest-only option. They also do more to explain to subjects that the PLS product is essentially a lottery, which raises concerns about priming. Additionally, they offer subjects a choice between a PLS product and a lottery ticket, but by design, their PLS option second order stochastically dominates the lottery.

[8]However, in this study there is a confound in the experimental design between the presence of downside risk and the timing of payments, which casts doubt on their interpretation. Specifically, the only questions in their experiment in which subjects frequently chose the early payment was for questions of the form: $20 now versus $28 or $16 with equal probability later. Therefore, it is unclear whether the effect is driven by the presence of risk alone or by the fact that it is possible to earn less money than by taking the safe, early payment. In any case, our experiment does not include downside risk, so our results are not necessarily in

The second main contribution of this paper is to use the observations from our experiment to jointly estimate decision-problem parameters under well-specified modeling assumptions. Specifically, we assume decision makers have a CRRA utility function and weight probabilities according to a Prelec (1998) probability weighting function.[9] As first pointed out by Yaari (1987), in models with probability weighting, one's risk attitude cannot be solely described by the curvature of the utility function, but rather, the shape of the utility function together with probability weighting jointly determine the risk attitude of a decision maker. In addition, Andersen, Harrison, Lau, and Rutström (2008) have demonstrated the importance of joint elicitation of risk and time preferences. Building on these insights, we designed our experiment to facilitate the joint elicitation and estimation of the various decision problem parameters. We adopt the theoretical framework and structural maximum likelihood methods of Andersen et al. (2008) to estimate jointly the consumer's discount factor, CRRA weighting parameter, and the Prelec probability weighting parameter.[10] Under the assumption of linear probability weighting, our structural estimation finds that subjects are both patient and modestly risk averse with results qualitatively similar to Andreoni and Sprenger (2012). However, our results also show that a model that allows for non-linear probability weighting fits the data substantially better. We also show that our model based on non-linear probability weighting provides a better fit to the data than one which assumes that decision makers have a direct preference for positively skewed assets. Moreover, we show that our main results are robust to unobserved heterogeneity.

The third main contribution of this paper is to use our structural estimates in simulations designed to estimate the response to the offer of PLS in some simple consumption-savings problems. We consider the relative effectiveness of PLS products as compared to standard savings products. We first show theoretically that, when given a choice between an interest-only device and a PLS device with the same expected return, there is always a prize large enough (with correspondingly small probability) such that a decision maker with non-linear probability weights prefers the PLS option. We then consider a simple intertemporal choice setting in which a risk averse decision maker with non-linear probability weights chooses between present and future consumption, where future consumption can come from a combination of interest-only savings or PLS savings with the same expected return. We show

contradiction to Anderson and Stafford (2009).

[9]Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978) were the first to show that subjects tend to over-estimate rare events. Following the cumulative prospect theory of Tversky and Kahneman (1992), many studies, including Gonzalez and Wu (1999), Abdellaoui (2000) and Bruhin, Fehr-Duda, and Epper (2010) have found strong experimental support for an inverse $S-$shaped probability weighting function. Unlike our setting, these papers only consider choices over lotteries at a fixed point in time.

[10] Stott (2006) finds that among 256 models, Prelec's one-parameter weighting function is preferable to its two-parameter version and to other non-parametric models when combined with a CRRA utility function.

that when the probability of receiving the prize is less than a threshold, the decision maker will allocate all future consumption to PLS. A corollary of these results is that the decision maker will allocate more to future consumption when PLS is available than when only interest is available. Given our structural estimation results, we find that a 0.01% probability of receiving a large prize causes subjects to increase their savings by about 4% relative to an interest only savings device with equal expected return. We show that men increase their savings more than women; those who purchase lottery tickets increase more so than those who do not; and that those with lower savings increase their savings more than those with higher savings, though the latter result is not statistically significant at conventional levels.

Before proceeding, we address the question of external validity of our results based on a laboratory study on a population of student subjects. We want to stress that we do not claim that, for example, the offer of PLS in the general population would increase savings by the same 4% suggested by our structural estimates. To be sure, there are likely substantial differences between our subject population and the general population at large, or even a target group of low savers, which would lead to a different response to PLS than what we estimate. Rather, our paper should be seen as showing that savings can be increased by making the delayed payment risky. Nevertheless, it is worth mentioning that lab and field experiments can give consistent results when a similar estimation method is used such as Laury, McInnes, and Swarthout (2012) and Andersen et al. (2008), though in general it is common for point estimates to vary across lab and field experiments and to vary significantly even within field experiments. In this paper, we offer a mechanism – non-linear probability weighting– for the attractiveness of PLS. This underlying mechanism appears to be a fundamental decision bias that arises in a number of studies using laboratory, field and other data and, therefore, can be reasonably expected to be present in a target population of people with low savings within the general public. Hence, this paper should be seen as providing a proof of concept that savings can be increased by providing risky returns, and the attractiveness of PLS can reasonably be expected to be present in the broader population. We leave it to future work to document the magnitude of the effect in a more representative population

In the next section, we provide details on our experimental design. In Section 3 we present descriptive results from our experimental data. In Section 4 we describe our structural estimation approach and results. In Section 5 we first show theoretically that non-linear probability weighting implies that PLS savings devices are preferred to interest-only devices and that they induce greater savings (for small enough probabilities/large enough prizes). We then conduct a number of numerical simulations using our earlier parameter estimates to quantify the effects of introducing PLS savings devices. Section 6 concludes.

2 The Experiment

Our experiment is designed with two goals in mind. First, we are interested in observing whether savings behavior responds more to lottery, or stochastic, interest payments than to guaranteed interest payments of the same expected value. Second, we aim to estimate structural parameters of a choice problem which involves tradeoffs over time and across different degrees of risk and uncertainty. We estimate these structural parameters by jointly eliciting risk and time preferences in the manner of Andersen et al. (2008). Later, we use the estimated structural parameters to estimate the effect of the offer of PLS on savings. As a broad overview, each subject was given a set of 100 binary choices – ten decision problems, each with ten questions – which can be used to infer risk and time preferences. The decision problems were of two types: seven prize-linked savings decision problems, including a set of standard time discounting questions, and three standard Holt and Laury (2002) risk-decision problems used to isolate risk preferences. We designed this combination of questions to show whether the offer of PLS leads to more savings than the offer of a standard interest account, and to learn how behavioral responses to PLS derive from underlying preferences (e.g. whether subjects respond to PLS because they behave as if they weight probabilities linearly and have risk-seeking preferences, or engage in non-linear probability weighting with risk averse preferences). The various problems were designed to make choices that isolate parameters governing discounting, risk-preferences and probabilty weighting.

2.1 Prize Linked Savings Decision Problems

The set of choices that constitute the main experimental contribution of this project are the seven prize-linked savings decision problems. The crucial aspect of these problems is that they presented subjects with the option of a certain payment early (Option A) versus a payment with interest later (Option B). Table 1 presents these seven sets of decision problems. The first set (a) is characterized by the choice between a certain payment early versus a certain payment later, where early and later refer to 3 and 5 weeks from the date of the experiment, respectively. All of the payments are scheduled to be in the future. The practical reason for this design is so that our estimation procedure is not encumbered by having to estimate hyperbolic discounting parameters.[11] The specific questions in decision problem set (a) involve the choice between Option A, a fixed amount of $20 paid in 3 weeks

[11]Of course, lack of an immediate reward only obviates the need to estimate a model of quasi-hyperbolic discounting; more general forms of non-exponential discounting may still be present. As a robustness check to our structural model, reported in Section 4, we estimated a specific form of hyperbolic discounting, based on Andersen, Harrison, Lau, and Rutström (2011b) and were unable to reject the null hypothesis of exponential discounting.

versus Option B, which adds a guaranteed interest payment, ranging from \$1 to \$10, to be paid in 5 weeks. This set of questions constitutes standard time discounting questions, and we expect a greater interest payment to induce greater rates of savings behavior (or delayed payment).

More interestingly, decision problems (b) and (c) present the choice between a certain early payment of \$20 in 3 weeks, and a binary lottery payment in 5 weeks. Questions (1) - (10) in these two sets of problems involve expected interest payments of equal value to the corresponding question in problem set (a), but the payment is stochastic in nature. To explain the notation, take, for example, question (1) of problem set (b): the notation $[(30, 20); (0.10, 0.90)]$ represents a lottery with a 10% chance of winning \$30 and a 90% chance of winning \$20, for an expected payment of \$21.[12]

In general, looking at decision problems (a) - (c), the i^{th} question for problem (a) corresponds to a choice of \$20 in three weeks or $\$20 + i$ in five weeks; this is precisely the expected value of Option B for the i^{th} question for both decision problems (b) and (c). Therefore, if the non-linear probability weighting is ruled out, a risk neutral decision maker should have the same switching point (sp) for all three decision problems, meaning they would move from early to later payment at the same expected interest payment in all three cases. Similarly, a risk averse decision maker with *linear* probability weighting would require an additional payment to take the risky option, and hence would be expected to switch later in problems (b) and (c). The lottery payment offered in problem set (c) is riskier than in (b); therefore, we would also expect a later switching point in problem (c). That is, under the assumption of a neoclassical risk averse decision maker, $sp(a) \leq sp(b) \leq sp(c)$. However, if, as many previous studies have found, subjects over-weight low probability events, then this should increase the attractiveness of Option B in the choice problems that involve a lottery payment. If the switching points (to delayed payment) are found to be earlier in sets (b) and (c), as compared to set (a), that would provide evidence suggesting that prize-linked savings products could be an effective way to entice individuals to save.

Observe in Table 1 that decision problems (d) – (f) have the same general characteristics as decision problems (a) – (c). Two alterations are that the base payment is \$15 and the payment dates are in 2 weeks for Option A and in 6 weeks for Option B. A fourth problem set (g) is added in this series to allow us to make comparisons with higher prize and lower probability lotteries. The two riskier lotteries in this set involve a top payoff of \$115 in problem set (f) and \$215 in problem set (g). Crucially, the odds adjust accordingly, so that the expected interest payment remains constant across the i^{th} question for all sets (d) – (g).

[12]The low prize of Option B being equal to the sure payment of Option A can be thought of as precautionary saving or security of principal à la PLS.

Table 1: Prize-Linked Savings Decision Problems

(a) Standard Time

Option A (3 weeks)	Option B (5 weeks)
20	21
20	22
20	23
20	24
20	25
20	26
20	27
20	28
20	29
20	30

(b) Certain Early vs. Later Lottery

Option A (3 weeks)	Option B (5 weeks)
20	(30, 20); (0.10, 0.90)
20	(30, 20); (0.20, 0.80)
20	(30, 20); (0.30, 0.70)
20	(30, 20); (0.40, 0.60)
20	(30, 20); (0.50, 0.50)
20	(30, 20); (0.60, 0.40)
20	(30, 20); (0.70, 0.30)
20	(30, 20); (0.80, 0.20)
20	(30, 20); (0.90, 0.10)
20	(30, 20); (1.00, 0.00)

(c) Certain Early vs. Later Lottery

Option A (3 weeks)	Option B (5 weeks)
20	(120, 20); (0.01, 0.99)
20	(120, 20); (0.02, 0.98)
20	(120, 20); (0.03, 0.97)
20	(120, 20); (0.04, 0.96)
20	(120, 20); (0.05, 0.95)
20	(120, 20); (0.06, 0.94)
20	(120, 20); (0.07, 0.93)
20	(120, 20); (0.08, 0.92)
20	(120, 20); (0.09, 0.91)
20	(120, 20); (0.10, 0.90)

(d) Standard Time

Option A (2 weeks)	Option B (6 weeks)
15	16
15	17
15	18
15	19
15	20
15	21
15	22
15	23
15	24
15	25

(e) Certain Early vs. Later Lottery

Option A (2 weeks)	Option B (6 weeks)
15	(25, 15); (0.10, 0.90)
15	(25, 15); (0.20, 0.80)
15	(25, 15); (0.30, 0.70)
15	(25, 15); (0.40, 0.60)
15	(25, 15); (0.50, 0.50)
15	(25, 15); (0.60, 0.40)
15	(25, 15); (0.70, 0.30)
15	(25, 15); (0.80, 0.20)
15	(25, 15); (0.90, 0.10)
15	(25, 15); (1.00, 0.00)

(f) Certain Early vs. Later Lottery

Option A (2 weeks)	Option B (6 weeks)
15	(115, 15); (0.01, 0.99)
15	(115, 15); (0.02, 0.98)
15	(115, 15); (0.03, 0.97)
15	(115, 15); (0.04, 0.96)
15	(115, 15); (0.05, 0.95)
15	(115, 15); (0.06, 0.94)
15	(115, 15); (0.07, 0.93)
15	(115, 15); (0.08, 0.92)
15	(115, 15); (0.09, 0.91)
15	(115, 15); (0.10, 0.90)

(g) Certain Early vs. Later Lottery

Option A (3 weeks)	Option B (5 weeks)
15	(215, 15); (0.005, 0.995)
15	(215, 15); (0.010, 0.990)
15	(215, 15); (0.015, 0.985)
15	(215, 15); (0.020, 0.980)
15	(215, 15); (0.025, 0.975)
15	(215, 15); (0.030, 0.970)
15	(215, 15); (0.035, 0.965)
15	(215, 15); (0.040, 0.960)
15	(215, 15); (0.045, 0.955)
15	(215, 15); (0.050, 0.950)

2.2 Risk Decision Problems

In addition to the prize linked savings problems described above, subjects were presented with three sets of risk decision problems. These are not relevant to the specific question of the appeal of prize-linked savings products, but they are necessary to elicit risk preferences separately from discount rates, which will help to identify the underlying reason for any attractiveness of PLS that we find.

Table 2: Risk Decision Problems

(h) Standard Holt-Laury

Option A (2 weeks)	Option B (2 weeks)
(25, 21); (0.10, 0.90)	(43, 7); (0.10, 0.90)
(25, 21); (0.20, 0.80)	(43, 7); (0.20, 0.80)
(25, 21); (0.30, 0.70)	(43, 7); (0.30, 0.70)
(25, 21); (0.40, 0.60)	(43, 7); (0.40, 0.60)
(25, 21); (0.50, 0.50)	(43, 7); (0.50, 0.50)
(25, 21); (0.60, 0.40)	(43, 7); (0.60, 0.40)
(25, 21); (0.70, 0.30)	(43, 7); (0.70, 0.30)
(25, 21); (0.80, 0.20)	(43, 7); (0.80, 0.20)
(25, 21); (0.90, 0.10)	(43, 7); (0.90, 0.10)
(25, 21); (1.00, 0.00)	(43, 7); (1.00, 0.00)

(i) Standard Holt-Laury

Option A (6 weeks)	Option B (6 weeks)
(20, 15); (0.005, 0.995)	(400, 7); (0.005, 0.995)
(20, 15); (0.010, 0.990)	(400, 7); (0.010, 0.990)
(20, 15); (0.015, 0.985)	(400, 7); (0.015, 0.985)
(20, 15); (0.020, 0.980)	(400, 7); (0.020, 0.980)
(20, 15); (0.025, 0.975)	(400, 7); (0.025, 0.975)
(20, 15); (0.030, 0.970)	(400, 7); (0.030, 0.970)
(20, 15); (0.035, 0.965)	(400, 7); (0.035, 0.965)
(20, 15); (0.040, 0.960)	(400, 7); (0.040, 0.960)
(20, 15); (0.045, 0.955)	(400, 7); (0.045, 0.955)
(20, 15); (0.050, 0.950)	(400, 7); (0.050, 0.950)

(j) Standard Holt-Laury

Option A (6 weeks)	Option B (6 weeks)
(22, 14); (0.01, 0.99)	(150, 8); (0.01, 0.99)
(22, 14); (0.02, 0.98)	(150, 8); (0.02, 0.98)
(22, 14); (0.03, 0.97)	(150, 8); (0.03, 0.97)
(22, 14); (0.04, 0.96)	(150, 8); (0.04, 0.96)
(22, 14); (0.05, 0.95)	(150, 8); (0.05, 0.95)
(22, 14); (0.06, 0.94)	(150, 8); (0.06, 0.94)
(22, 14); (0.07, 0.93)	(150, 8); (0.07, 0.93)
(22, 14); (0.08, 0.92)	(150, 8); (0.08, 0.92)
(22, 14); (0.09, 0.91)	(150, 8); (0.09, 0.91)
(22, 14); (0.10, 0.90)	(150, 8); (0.10, 0.90)

Table 2 presents these choice sets, labeled as problem sets (h), (i), and (j). Problem set (h) presents two lottery options, both paying out in two weeks. Problem sets (i) and (j) present two lotteries, both which pay out in six weeks. These are designed as standard risk elicitation problems, as introduced by Holt and Laury (2002) and have been used by many subsequent researchers, including Andersen et al. (2008). In these problems, the expected value of Option A is higher than the expected value of Option B in initial questions, before switching in later questions to favor Option B. For example, in problem set (h), in the first question, Option A has an expected value of 21.4 and Option B has an expected value of 10.6.

But Option B offers a top payoff of 43, as compared to a top prize of 25 in Option A. Only a sufficiently risk-loving consumer or someone with an extreme form of non-linear probability weighting would choose Option B in this question. A risk-neutral consumer should switch from choosing A to B when the expected value of Option B becomes greater, which occurs between questions 4 and 5 for all three problems, while a risk averse decision maker would switch later. In question 10 of set (h), Option A has an expected value of 25 and Option B has an expected value of 43. No rational subject who understands the instructions and is playing for real would choose Option A in this question.[13, 14]

One innovation of our experimental design as compared to previous experiments eliciting risk parameters is to include a wider range of probability values and prize values. The experimental literature that estimates the probability weighting in rank-dependent models often uses probabilities between 0.1 and 0.9 for the uncertain outcomes (Andersen et al. (2008), Harrison and Rutström (2008) when they analyzed Holt and Laury (2002)). In the questions included in our experiment, we extended the range of probabilities to include 0.005 and 0.995. This is important for us, because the main interest of our paper is on studying the relative attractiveness of PLS-type savings devices where subjects win large prizes with comparatively small probabilities. Such questions also allow us to better identify any non-linearity in the weighting of probabilities, something which is lacking in papers that only consider more intermediate probabilities.

2.3 Experimental Procedures

University of Maryland (UMD) undergraduate students were recruited to participate in this experiment in the UMD Department of Economics Experimental Laboratory.[15] A total of 96 students participated in one of six sessions held on 3/28/2012 and 3/29/2012.[16] Subjects were

[13] And, in fact, from Table 4, one can see that only 1 subject irrationally chose Option A at the 10th question.

[14] In designing the problems used in our experiment, we aimed to create problems that gave expected payoffs that were within the typical range of payments in the Experimental Economics Laboratory at the University of Maryland (between \$15 and \$20 per hour), and also to be consistent with the existing literature. For example, the range of payoffs in Andersen et al. (2008) was \$7.65-\$687 (and, in fact, subjects only had a 10% chance of being paid for one risk elicitation problem and a 10% chance of being paid for one time discounting problem), while in Holt and Laury (2002), the outcomes were \$40 or \$32 for Option A, and \$77 or \$2 for Option B. In the high payoff treatment the outcomes were \$180 or \$144 for Option A and \$346.50 or \$9 for option B.

[15] As in a typical experiment, in the advertisement of the experiment, the subjects were only informed that it was an experiment in decision making and they were not informed about the exact nature of the experiment. Additionally, no subject left the experiment after they read the instructions.

[16] We selected these dates so that the payment dates did not correspond to final exams week or a holiday.

presented with the experimental problems using individual, confidential computer kiosks.[17] The experiment was programmed in z-Tree (Fischbacher, 2007). A pen and paper survey was administered at the end of the session. Appendix A includes the experiment instructions, while Appendix B contains the survey. In addition to a $7 participation fee and $3 for completing the post-experiment survey, subjects were paid for one random decision.[18]

To determine which of the 100 decisions would be used to determine an individual student's additional payment, each subject rolled a 10-sided die twice, first to determine the decision problem and then to determine the question. After the specific question was determined, depending on the option chosen, subjects rolled the same die (up to three additional times) to determine their payment.[19] On average, based on their decisions in the experiment, subjects received $18.91 (min $7; max $120), with payments occurring 2, 3, 5 or 6 weeks after the experiment. After the payment amount and date were determined, the subjects wrote their name on the outside of an envelope and the payment amount and date on the inside of the envelope. The envelope was then returned to the experimenter, filled with the appropriate amount of money and locked in a secure location. The day before the payment date, subjects were sent an email reminding them that they could pick up their envelope the next day between 9:00am and 5:00pm. Note that regardless of the payment date, subjects would have to return to the experimental lab to receive their payment. Therefore, although the experiment imposed an additional cost on subjects, the cost was the same regardless of the payment date. All subjects came to receive their payments on their appointed day.

3 Basic Results

We begin our empirical analysis by presenting basic statistics on subject choices in the experiment. These results show how basic patterns in behavior varied across the different problems. Subjects' behavioral choices are captured succinctly by two measures: the fraction

[17]All subjects saw the problems in the same order; specifically, (a), (d), (e), (b), (f), (c), (g), (h), (i) and (j). Therefore, the standard interest questions were asked first, the PLS questions second and the risk elicitation questions last.

[18]Under a monotonicity assumption, Azriele, Chambers, and Healy (2012) show that this is (essentially) the only incentive compatible mechanism to pay subjects. Cubitt, Starmer, and Sugden (1998) show that this incentive scheme generates reliable experimental data (see also Azriele et al. (2012) for further discussion and references). For a contrasting view, see Harrison and Swarthout (2014) who highlight issues with this payment mechanism for experiments testing for violations of the independence axiom.

[19]In our experiment, all uncertainty was resolved within the experimental lab, while the subjects were required to wait between 2 and 6 weeks for their experimental earnings. One might wonder whether this has any influence on our results. Indeed, existing experimental literature shows that subjects have preference for late resolution of uncertainty when probability of winning the prize is small (see, e.g., Chew and Ho (1994) and Ahlbrecht and Weber (1997b)). In our setting, such a bias would make PLS even more attractive. Thus, the response to PLS that we identify should be seen as being on the conservative side.

of subjects who chose to delay payment (i.e., chose option B) in each problem, and the average switch point for each problem. We define the switch point to be the first question at which the subject chose option B. Recall that there are 10 questions, and that they are ordered so that once a subject chooses option B it is not rational to choose option A later.[20]

3.1 PLS and the Decision to Save

Table 3 presents the results of the decision problems featuring PLS and standard interest options. The top panel of the table shows results for problems (a) – (c) and the bottom panel shows results for problems (d) – (g). A large fraction of subjects chose to delay payment, or to save. In particular, in problem (a) almost half of the subjects (47 percent) were willing to wait an extra two weeks for one additional guaranteed dollar, and in problem (d) 38 percent of the subjects were willing to wait an extra 4 weeks for one guaranteed additional dollar.[21] For these subjects, all we can conclude from their immediate choice to save is that they needed *less* than one additional dollar to induce them to switch to the delayed payment; that is, we have an upper bound on their level of impatience. Observe also that despite the generous interest offered, 10% of subjects in problem (d) still chose the early payment of \$15 in two weeks versus \$25 in six weeks. Thus, there is an extremely wide range of time preferences represented in our sample.

The problems are designed so that it is natural to compare the PLS problems (b) and (c) to the standard interest problem (a), and to compare PLS problems (e), (f) and (g) to the standard interest problem (d). Considering the delayed payment option in each case, problem (c) is a mean-preserving spread of problem (b), which is a mean preserving spread of problem (a). Similarly, problem (f) is a mean-preserving spread of (e), which is a mean-preserving spread of (d).[22] Thus, standard expected utility theory predicts that a risk-averse decision maker without non-linear probability weighting should prefer option B in a given question of problem (a) over the option B of the same question in problems (b) and (c). The similar comparison holds for problem (d) and problems (e) and (f). Our empirical findings are in direct contrast to this prediction. These results reject the standard model in which a risk averse agent maximizes expected utility (i.e. linear probability weighting).

Comparing the PLS problems to their corresponding standard certain interest problems,

[20]Only four subjects chose option A after previously choosing option B on any problem. Since the switch point is not clearly defined for these subjects, we excluded them from the switch point regressions.

[21] Perhaps this revealed patience reflects, in part, our experiment's focus on future payment times exclusively. No question offered the option of immediate payment, so the design of the experiment explicitly avoided a role for present-biased preferences.

[22]Problems (f) and (g) vary on two dimensions – variance and the delay of the payment. This was done to better identify the parameters of the utility function in the structural estimation.

Table 3: Savings rate and switch point responses to PLS v. standard interest questions

(i) Problems (a) - (c)

	Std. Int.	PLS	PLS
Problem	(a)	(b)	(c)
Fraction delay payment: Question 1	0.47	0.63^{***}	0.69^{***}
Fraction delay payment: All questions	0.76	0.82^{***}	0.81^{*}
Average switch point (s.d.)	3.4 (2.9)	2.7^{***} (2.7)	2.9 (3.3)
Median switch point	2	1	1
Fraction never switching	0.04	0.01	0.01

(ii) Problems (d) - (g)

	Std. Int.	PLS	PLS	PLS
Problem	(d)	(e)	(f)	(g)
Fraction delay payment: Question 1	0.38	0.54^{***}	0.66^{***}	0.71^{***}
Fraction delay payment: All questions	0.68	0.77^{***}	0.81^{***}	0.81^{***}
Average switch point (s.d.)	4.1 (3.4)	3.3^{***} (3.1)	2.8^{***} (3.2)	3.0^{***} (3.5)
Median switch point	3	1	1	1
Fraction never switching	0.10	0.03	0.01	0.03

Notes: Asterisks indicate level of significance for $t-$test of equality relative to the corresponding standard interest problem (a v. b, c; d v. e, f, g). $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.10$.

we find that subjects were more likely to save when presented with PLS opportunities. Whereas 47 percent of subjects chose to delay payment at question 1 of problem (a), 63 and 69 percent of subjects chose to delay payment at question 1 of the PLS problems (b) and (c), respectively. These PLS savings rates were significantly greater than the savings rate for problem (a) ($p < 0.001$). We find a similar pattern when we compare initial savings rates for problems (e) and (f), which presented savings choices with payments that were delayed longer relative to problem (d). Whereas 38 percent of subjects chose to delay payment at question 1 of problem (d), 54 and 66 percent of subjects chose to delay payment at question 1 of the PLS problems (e) and (f), respectively. It is more difficult to compare the results from problem (g) to any one standard saving problem because the stakes are similar to problem (d) and the time horizon is similar to problem (a). However, the pattern of behavior matches what we see for the other PLS problems. 71 percent of subjects chose to delay payment at the first question of problem (g).

We observed a similar pattern when we considered the responses to all ten questions.

Whereas 76 percent of choices were for option B, the delayed payment, for the standard interest problem (a), 82 and 81 percent of choices were for option B in the corresponding PLS problems, (b) and (c) respectively. The former is statistically different from the rate for problem (a) at the 1-percent level; the latter at the 10-percent level. Similarly, whereas 68 percent of choices were for delayed payment for the standard interest problem (d), 77, 81 and 81 percent of choices were to delay payment in the corresponding PLS problems, (e), (f) and (g) respectively. All three of these rates are significantly distinct from the rate for option (d) at the 1-percent level.

The design of the experiment allows us to measure another dimension along which savings responses to PLS and standard interest offerings were different. The incremental variation in the questions allows us to measure the minimum expected return necessary to induce initial non-savers to choose to save. In each problem, subsequent questions offered higher expected returns to the saving option, in the form of a higher certain payment in problems (a) and (d), and in the form of an increased probability of a high payment in the PLS problems. The expected return to choosing option B increased from question 1-10 in the same way for problems (a) – (c), and for problems (d) – (g).

For each problem, by the time subjects reached question 10, which offered the highest expected returns for option B, the vast majority chose to save. There was significant variation, however, in how high an expected return was necessary to induce subjects to save. To document this variation, we present the average (and standard deviation) of the switch point for each problem. The switch points for problems (a) – (c) are shown in the third row of Table 3. On average when presented with problem (a), subjects switched to option B after 3.4 questions. There was also a good deal of variation in switch points. The standard deviation in switch points for problem (a), for example, was 2.9, suggesting that there was a significant amount of heterogeneity in saving preferences.

In comparison, the switch points for the PLS problems (b) and (c) (2.7 and 2.9, respectively) were earlier on average than for the standard interest problem (a). In other words, PLS required lower expected returns to induce subjects to save. The p-values of the differences in switch points relative to problem (a) were less than 0.001 and 0.111, respectively.

We observe similar patterns in the switch points for problems (d) – (g). The average switch point for the standard interest problem (d) was 4.1. The average switch points for the three PLS problems with corresponding expected returns were significantly earlier. The average switch points for problems (e) – (g) were 3.3, 2.8 and 3.0, respectively. Each was statistically significantly different from problem (d)'s switch point ($p < 0.001$ in each case).

Taken together, these results demonstrate that PLS induced more saving behavior than standard interest. Subjects were more likely to save when presented with the initial PLS choice than when presented with the initial standard interest choice. Furthermore, lower expected returns were required to induce subjects to save when the returns were presented as PLS than when they were presented as standard certain interest.

3.2 Risk Elicitation Problems

The above results show that PLS increased savings by our subjects; however, they do not allow us to distinguish between which of two underlying causes lead to the result: convex utility or non-linear probability weighting. Problems (h)–(j) are standard Holt-Laury problems that gave subjects a choice between a safer option and a riskier option. In each problem, both options paid off with the same delay. To resolve this issue, we now turn to the results for the risk elicitation problems. In all three of our risk problems, a risk-neutral decision maker with linear probability weights would switch between the fourth and fifth question. Both convex utility and non-linear probability weighting would lead to earlier switch points, while concave utility would lead to later switch points.[23] Table 4 provides the summary results. The main finding is that for all three problems, the switch point occurs significantly later than the fifth question according to a Wilcoxon signed-rank test ($p < 0.01$ in all cases). Thus, it must be that subjects' utility is concave in money. Assuming that subjects have stable preferences across different decision problems, this implies that non-linear probability weighting is more likely to explain subjects' choices with respect to PLS than convex utilities.

Table 4: Summary Statistics: Risk Elicitation Problems

Problem	(h)	(i)	(j)
Fraction risky gamble: Question 1	0.00	0.30	0.26
Fraction risky gamble: All questions	0.41	0.48	0.49
Average switch point (s.d.)	6.9 (1.4)	6.3 (4.0)	6.2 (3.7)
Median switch point	7	7.5	6
Fraction never switching	0.01	0.17	0.09

3.3 Heterogeneity in responses to PLS

The results in Table 3 also suggest significant heterogeneity across subjects in savings preferences. We next examine how savings choices and preferences towards PLS varied across subjects. In particular, we explore heterogeneity across three dimensions: (a) self-reported

[23]Concave utility and non-linear probability weighting push the switching point in opposite directions with respect to the switch point of a decision maker with risk neutral and linear probability weighting.

lottery players versus self-reported lottery abstainers; (b) male versus female; and (c) those with a combined balance in their savings and checking accounts of more or less than \$1000. In our study sample, gender and lottery status were correlated, but neither was strongly correlated with having a high account balance. Female subjects were less likely than male subjects to be lottery players (21 versus 50 percent). About half of lottery abstainers were female, whereas 82 percent of lottery players were male. In Table C.2 in Appendix C, we repeat this analysis for other variables of potential interest that were obtained from our survey. For comparisons based on these additional variables, we are unable to reject the null hypothesis that the effect of PLS is the same (for each of the 10 variables considered, $p \gg 0.1$ in all cases).

Table 5 presents estimated effects of PLS on the two outcomes – savings rates and switch points – separately by status for each of these three comparison sets. Panel (i) reports effects and differences by lottery status; panel (ii) reports effects and differences by gender; and panel (iii) reports effects and differences by savings status (high/low). The first column reports the share of the sample defined by the particular characteristic. The second column reports the difference in the fraction of the respective group who chose option B in the PLS problems relative to the same fraction for the standard interest problems, as estimated by a regression that pools responses from questions (a) – (g). The third column reports the PLS-standard interest difference in average switch points. Rows 1-2, 4-5 and 7-8 report simple PLS-standard interest differences in the relevant outcome. Row 3 reports the difference-in-differences, defined to be the lottery PLS-standard interest difference minus the non-lottery PLS-standard interest difference, and similarly for rows 6 and 9.[24,25]

Lottery players were 16.3 percent more likely to save when presented with a PLS option than when presented with a standard interest savings option. Lottery players who did not

[24]All reported coefficients are estimated from regressions of an indicator for choosing option B ("Delay payment") or the switch point on an indicator for the PLS questions interacted with indicators for both mutually exclusive groups (e.g. males and females) and an indicator for one of the groups (i.e. lottery player, female, high savings). The estimates shown in rows 1-2, 4-5 and 7-8 report the coefficient on the interactions of the PLS indicator and the group indicators. The estimates shown in rows 3, 6 and 9 show the estimated difference in the estimated PLS effect between the two groups (e.g. male and female). All regressions reported in the table also allow a different intercept for problems (a) – (c) versus problems (d) – (g), and only include responses to problems (a) – (g). In the "Delayed payment" regressions, an observation is a question answered by a subject in a problem. In the "switch point" regressions, observations are at the problem by subject level.

[25]We also investigate whether there is any cross-sectional variation in the distributions of switch points. To do this, we compute the change in switch point for all binary comparisons (e.g., (a) vs. (b), (a) vs. (c), (d) vs. (e), etc) and then sum these numbers up. We then test whether the medians, means or distributions were different for different subgroups such as those reported in Table 5. Doing this exercise for means ($t-$test) and medians (Mann-Whitney test) gives the same results as in the table: a significant effect for gender and lottery status and a just insignificant effect on savings ($p = .126$). The Epps-Singleton test for distributions also gives the same significance patterns for those three categories.

Table 5: Differential response to the introduction of PLS (v. standard interest) based on observable characteristics

			PLS v. Standard interest	
	Subgroup:	Share of sample	Δ Delay payment	Δ Switch point
	Lottery player	0.396	0.163***	−1.621***
			(0.037)	(0.395)
(i)	Not lottery player	0.604	0.040**	−0.347*
			(0.018)	(0.181)
	Lottery − Not		0.122***	−1.274***
	(Δ − in − Δ)		(0.042)	(0.436)
	Female	0.354	0.024	−0.138
			(0.030)	(0.303)
(ii)	Male	0.646	0.124***	−1.223***
			(0.024)	(0.248)
	Female − male		−0.110**	1.085***
	(Δ − in − Δ)		(0.038)	(0.393)
	Savings > \$1000	0.490	0.058**	−0.544*
			(0.028)	(0.282)
(iii)	Savings $\leq$ \$1000	0.510	0.118***	−1.146***
			(0.026)	(0.279)
	High/low savings		−0.060	−0.602
	(Δ − in − Δ)		(0.038)	(0.397)
	N		6720	644

Note: Each entry in rows 1, 2, 4, 5, 7 and 8 is the difference in the fraction of subjects choosing option B (column 1) or the difference in average switch point (column 2) in PLS versus standard interest questions. PLS questions b and c are compared with standard interest question a; PLS questions e, f and g are compared with standard interest question d. The differences are estimated in an OLS regression that pools responses from questions a-g. The entries in rows 3, 6 and 9 show the difference-in-difference from the introduction of PLS (versus standard interest) for the comparison sub-populations: lottery and non-lottery players (row 3), female and male subjects (row 6), and between subjects with more and less than \$1000 in their checking and savings accounts (row 9). "Savings > \$1000" is an indicator for subjects whose combined reported savings plus checking account balance is greater than \$1000. Standard errors reported in parentheses are robust to heteroskedasticity and account for subject-level correlation in random errors. Asterisks indicate standard levels of statistical significance. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

initially choose to save in question 1 also required a lower expected return to be induced to save when it came in the form of PLS as compared with standard interest. On average, lottery players switched from option A to option B 1.6 questions earlier when presented with a PLS option than when presented with a standard interest option. Both of these PLS-standard interest differences were statistically significant at the 1-percent level. Subjects who did not report being regular lottery players exhibited similar patterns, though the magnitudes of the differences were significantly less pronounced. Lottery non-players were 4.0 percent more likely to save when presented with PLS as compared with standard interest options; they switched from non-saving to saving on average 0.3 questions earlier when faced with PLS as compared with standard interest options. The third row shows the difference in these differences between lottery players and non-players. Both differences are statistically distinguishable from zero: Lottery players were induced to save more by PLS, and required lower expected returns to be induced to save by PLS.[26]

The next panel of the table shows results broken out by gender. Females showed no differential savings response to PLS versus standard interest. Similarly, switch points among female subjects were not significantly different for PLS and standard interest problems. In contrast, male subjects were more likely to save when presented with PLS savings options (12.4 percent higher savings rates, $p < 0.01$) and among male subjects significantly lower expected returns were necessary to induce a switch from not saving to saving when the returns were in the form of PLS than when they were presented as standard interest (average switch point 1.2 questions earlier, $p < 0.01$). The difference in differences (PLS v. standard interest, female v. male) for the fraction choosing to save and the switch point were significant at the 5 percent and 1 percent levels, respectively.[27]

One motivation for PLS is that it might induce saving among individuals who do not currently save much. Support for this hypothesis comes from two facts: low-income individuals have very low savings rates, but devote a disproportionate amount of their expenditures to lottery tickets (Kearney (2005)). Because the experimental sample was drawn from undergraduates, we are not able to meaningfully compare subjects based on current or permanent income. Instead, to address this question, we compare subjects based on their reported savings. The bottom panel of the table shows results broken out between subjects who reported a combined checking and savings account balance of greater than \$1000 versus those who reported a balance less than or equal to \$1000.[28] This split divides the sample essentially in half. Among each group, we observed stronger savings responses to PLS than to stan-

[26] Guryan and Kearney (2008) provide evidence of misperceptions of probabilities among lottery players, though that work documents an apparent belief in winning "streaks" or more specifically "lucky stores" and does not examine overweighting in particular.

[27] Previous studies have found that women tend to avoid risky options more than men (e.g. Croson and Gneezy (2009)). Fehr-Duda, de Gennaro, and Schubert (2006) and Booij, van Praag, and van de Kuilen (2010) find that differences in probability weighting rather than risk parameters account for more risk averse behavior observed in women.

[28] Admittedly, this is an arbitrary distinction, but given our subject pool consists entirely of undergraduate students, we presume that few are accumulating assets in the form of real estate or stocks and that most are saving for short-term goals. Having \$1,000 in savings thus seemed like a potentially relevant measure. Table C.2 repeats the analysis when we also consider savings net of any credit card balance. The differential response between those with more or less than \$1000 in net account balances is weaker in this case than when credit card balances are excluded—apparently because the few subjects with positive credit card balances do not respond to PLS.

dard interest. Subjects with more than \$1000 in combined balances saved 5.8 percent more often when presented with PLS than when presented with standard interest options. The corresponding difference was 11.8 percent among subjects with combined balances less than \$1000. The difference in these relative responses to PLS is not significant at conventional levels, but the p-value of the difference was 0.12. We saw a similar pattern for switch points. Among subjects with more than \$1000 in combined savings, switch points were 0.5 questions earlier for PLS than standard interest problems. Among those with less than \$1000, switch points were 1.1 questions earlier. The double difference in switch points was not statistically significant at conventional levels, but the p-value of the difference was 0.13. The results presented in Table 5 demonstrate that responses to PLS were stronger among lottery players than among lottery abstainers, among males than among females, and among those with low savings/checking account balances than among those with high account balances. The correlation in these characteristics – particularly the relationship between gender and lottery play – raises the possibility that a pair-wise comparison picks up the heterogeneity in responses to PLS associated with a correlated characteristic (e.g. that the male-female difference in response is driven by the male-female difference in lottery play). We explored this question by estimating a regression model that allowed responses to PLS to vary by gender, lottery status and savings/checking account status simultaneously. Specifically, we estimated regressions in which the dependent variable was either an indicator for choosing option B or the switch point and the regressors were an indicator for PLS, indicators for female, lottery player, and $>$ \$1000 in combined savings, and interactions between the PLS indicator and each of the three heterogeneity indicators. The results from those two regressions are presented in Appendix Table C.1 and are qualitatively the same as the results presented in Table 5. Holding constant gender and savings account status, lottery players were relatively more responsive to PLS than non-lottery players. Holding constant lottery status and savings account status, female subjects were relatively less responsive to PLS than males. Holding constant gender and lottery status, subjects with less than \$1000 in combined savings and checking accounts were relatively more responsive to PLS than those with less than \$1000. The main difference is that while the effect of savings was marginally insignificant in Table 5 ($p = 0.13$), once controlling for gender and lottery status, the effect of savings is significant at he 5% level.

In Appendix Table C.2, we replicate the difference-in-difference analysis for eleven other subject characteristics that we learned from the survey. The only characteristic found to have a significant effect was having a positive credit card balance. In particular, the (small) group of subjects with a positive balance do not respond to PLS, while those with a zero balance increase savings in response to PLS. This finding is consistent with liquidity constrained subjects who prefer to take the money up front, in order to pay down debt, regardless of the type of savings vehicle offered to them. Other explanations are possible, but, unfortunately, we do not have enough data to distinguish them.

4 Structural Estimation of Choice Parameters

The results presented so far indicate that subjects, on average, chose to save more, and were induced to save with lower interest rates, by PLS than by standard savings accounts. We have also documented significant heterogeneity in relative preferences for PLS versus standard interest savings accounts. This heterogeneity points to variation in preferences for risk, discounting and other aspects of preferences (e.g., the weighting of probabilities and/or preferences for skewed distributions). The design of the experiment presents an opportunity to jointly measure these important underlying parameters and to try to distinguish between some competing explanations. In this section we estimate two structural models based on competing explanations for the behavior we observed: non-linear probability weighting or a direct preference for positively skewed assets. We will first show that the non-linear probability weighting model explains the data better. We then argue that its theoretical implications are more in line with the empirical evidence. Finally, we will use this model to examine how the estimated parameters vary along the dimensions shown in the heterogeneity analysis from the previous section, and extend it to the case of unobserved heterogeneity in the underlying parameters.

4.1 The Consumer Choice Problem

We seek to estimate the parameters of a model of consumer behavior under uncertainty in order to explain the observed patterns in our study and, in the next section, to consider the potential impact of PLS on savings behavior in several hypothetical consumption-savings decisions. When dealing with small probabilities of large gains, the applied literature suggests at least two different modeling approaches. First, as suggested by Prospect Theory, it may be that subjects *over-weight* small probabilities, which causes them to be attracted to assets with lottery-like returns. To operationalize this, one must simply extend the structural model of Andersen et al. (2008) to allow for non-linear probability weighting.[29] The basic elements are as follows:

[29]Other papers have adapted the structural estimation procedure of Andersen et al. (2008). See, for example, Coble and Lusk (2010), Andersen, Harrison, Lau, and Rutström (2011a) and Laury et al. (2012). The latter paper also examines non-linear probability weighting and fails to find evidence against linear probability weights, but this could be due to their use of intermediate probabilities.

(i) Subjects have a Bernoulli utility function of the form $u(x) = \frac{x^{1-\rho}-1}{1-\rho}$, where ρ is the risk parameter of the subject;[30,31]

(ii) Subjects weight objective probabilities non-linearly according to some weighting function $w(p)$. In what follows, we adopt the one-parameter form, $w(p) = e^{-(-\ln p)^{\alpha}}$ from Prelec (1998);[32]

(iii) Subjects discount payments received in the future with the interest rate $r \geq 0$.[33]

Therefore, the utility of a lottery, $\ell = [(x_1, x_2); (p_1, p_2); t]$, such that it pays at time t, x_1 with probability p_1, and x_2 with probability p_2 where $p_1 + p_2 = 1$ and $x_1 \geq x_2$ is

$$U(\ell; \Theta) = e^{-r \cdot t} \left(w(p_1) x_1^{1-\rho} + (1 - w(p_1)) x_2^{1-\rho} - 1 \right) / (1 - \rho)$$

where t is the time at which the subject would receive the payment if the given problem was randomly selected for payment. Θ denotes the vector of parameters that describe the decision maker's preferences.

This model has been used in a number of applied settings including, notably, by Barberis and Huang (2008) (though with a different probability weighting function and more general lotteries) where they show that non-linear probability weighting can explain the poor long-run performance of IPOs and other assets with positively skewed returns.

An alternative approach, which was recently taken by Mitton and Vorkink (2007), is to assume directly a preference for skewness of a lottery. In this case, the utility of lottery ℓ, which pays off at time t, is given by:

$$U(\ell; \Theta) = e^{-r \cdot t} \left(\mathbb{E}[\ell] - \frac{\tau}{2} \mathbb{V}[\ell] + \frac{\phi}{3} \mathrm{Skew}[\ell] \right),$$

where $\mathbb{E}[\cdot]$, $\mathbb{V}[\cdot]$ and $\mathrm{Skew}[\cdot]$ are the mean, variance and skewness operators, while $\tau > 0$ captures one's aversion to variance and $\phi > 0$ captures one's preference for positively skewed

[30] We adopt the form above rather than the more traditional form $\hat{u}(x) = \frac{x^{1-\rho}}{1-\rho}$ because $\lim_{\rho \to 1} u(x) = \log x$, while in the more traditional form, this is not the case.

[31] Following the literature, we call ρ the risk parameter, although, as previously noted, the risk preferences of a decision maker with non-linear probability weighting function cannot be measured solely by ρ.

[32] Recently, Hsu, Krajbich, Zhao, and Camerer (2009) have provided neuroeconomic evidence that subjects have a non-linear probability weighting function, and that the one parameter functional form suggested by Prelec (1998) fits the data quite well. See also Footnote 10.

[33] Note that in the interest of parsimony, we do not consider models with non-exponential discounting. The front-end delay for all problems obviates the need to consider quasi-hyperbolic discounting. We did estimate a model in which discounting is given by $e^{-rt^{1/s}}$. However, we were unable to reject that $s = 1$, which corresponds to exponential discounting. See Benhabib, Bisin, and Schotter (2010) and Andersen et al. (2011b) for more details and alternative specifications.

distributions.[34,35]

In order to estimate the parameters of the model, first we model the comparison between two lotteries ℓ_a and ℓ_b as follows: Let $\Delta_{ab}(\Theta) := U(\ell_a;\Theta) - U(\ell_b;\Theta)$ be an index function. Using a distribution function $F(\Delta_{ab}(\Theta))$, this index function is linked to the observed choices. This function maps any real number to a number in the interval $[0, 1]$. The probability that the decision maker chooses a lottery ℓ_a over ℓ_b is given by $Pr(\ell_a, \ell_b; \Theta) = F(\Delta_{ab}(\Theta))$. Luce (1959) shows that if we choose $F(\cdot)$ as the logistic CDF where λ is the inverse standard deviation parameter, then the probability that the decision maker i chooses a lottery ℓ_a over ℓ_b for question j is equal to the binary logit such that:

$$Pr^{ij}(l_a, l_b; \Theta, \lambda) = \frac{e^{\lambda U(l_a;\Theta)}}{e^{\lambda U(l_a;\Theta)} + e^{\lambda U(l_b;\Theta)}},$$

where λ can be interpreted as a rationality parameter. When $\lambda = 0$, $Pr(l_a, l_b; \Theta, \lambda) = 0.5$, implying that the decision maker disregards the utilities of the lotteries and picks one of the two choices at random. On the other hand, as $\lambda \to \infty$, the decision maker chooses the lottery that gives a higher utility. The higher λ, it is more likely that the decision maker will pick the lottery with a higher utility (see Harrison and Rutström (2008) for a summary of models of choice with error).

Finally, we can then write the likelihood function as:

$$L(\Theta, \lambda) = \prod_{i=1}^{N} \prod_{j=1}^{100} Pr^{ij}(l_a, l_b; \Theta, \lambda)^{\mathbf{1}_{[c_{ij}=l_a]}} (1 - Pr^{ij}(l_a, l_b; \Theta, \lambda))^{\mathbf{1}_{[c_{ij}=l_b]}} \tag{1}$$

where $c_{ij} \in \{l_a, l_b\}$ is the choice of the decision maker i for question j, and $\mathbf{1}_{[\cdot]}$ is the indicator function equal to 1 if the condition in $[\cdot]$ is satisfied, 0 otherwise.

[34]Skewness is defined as the ratio of the centered third moment to the variance. That is, $\text{Skew}[\ell] = \frac{\mathbb{E}[(\ell-\mu)^3]}{\mathbb{E}[(\ell-\mu)^2]}$.

[35]Yet another approach would be to take the optimal expectations model of Brunnermeier and Parker (2005). In this case, the decision maker cares about utility flows and, hence, there may be a benefit to being over-optimistic (which must be balanced against the utility cost of worse decision making). This model does not lend itself to a clear structural form that we can estimate, nor was our experiment, which only considers binary lotteries, designed to try to distinguish this model from the other two candidates discussed above (see, e.g., Roger (2011) for work in this direction). For this reason, we will not discuss it further except to say that the main implication is that the decision maker will generally become over-optimistic that the good state will occur, making the implications very similar to the model of non-linear probability weighting. One final possibility is to incorporate the entertainment value of gambling (see Conlisk (1993)). We estimated the parameters of the model with an additive entertainment value and linear probability weighting. The fit of this model was significantly worse than the model with non-linear probability weighting alone.

4.2 Estimation Results

4.2.1 Pooled Estimates

We begin by reporting results pooling the entire sample of subjects. Table 6 reports the maximum likelihood estimates.[36] Panel (a) reports results for the probability weighting model, while panel (b) reports results for the preference for skewness model. In each panel, in column (1), we assume that there is a single rationality parameter, λ, while in column (2), we allow for three possible rationality parameters: one for those problems (a) and (d) where all outcomes were certain ($\lambda_{\texttt{time}}$); one for the problems (b), (c), (e), (f) and (g) where Option B was uncertain ($\lambda_{\texttt{PLS}}$); and one for the risk decision problems (h), (i) and (j) ($\lambda_{\texttt{risk}}$). For the probability weighting model, the rationality parameters we estimate are quite similar, and a likelihood ratio test cannot reject that the λs are, in fact, the same at the 5% level ($LR(2) = 5.38$; $p = 0.068$). In contrast, having separate rationality parameters does significantly improve the fit in the preference for skewness model ($p \ll 0.01$).

Table 6: Estimation Results:

(a) Probability Weighting

Parameter		(1)	(2)
Risk Pref.	ρ	0.514	0.497
		[0.441, 0.586]	[0.418, 0.569]
Prob. Wgt.	α	0.752	0.768
		[0.697, 0.810]	[0.716, 0.825]
Int. Rate	r	0.834	0.856
		[0.335, 1.338]	[0.355, 1.357]
Rationality Params.	λ	1.641	
		[1.261, 2.158]	
	$\lambda_{\texttt{time}}$		1.470
			[1.083, 1.996]
	$\lambda_{\texttt{PLS}}$		1.651
			[1.241, 2.211]
	$\lambda_{\texttt{risk}}$		1.482
			[1.095, 1.997]
	obs	9600	9600
	LL	-4717.78	-4715.09

(b) Preference for Skewness

Parameter		(1)	(2)
Var. Pref.	τ	0.0019	0.0019
		[0.001, 0.003]	[0.001, 0.003]
Skew. Pref.	ϕ	0.713	0.591
		[0.358, 1.170]	[0.335, 0.858]
Int. Rate	r	0.523	1.374
		[0.000, 1.501]	[0.593, 2.136]
Rationality Params.	λ	273.12	
		[242.1, 314.6]	
	$\lambda_{\texttt{time}}$		346.72
			[275.4, 442.7]
	$\lambda_{\texttt{PLS}}$		400.83
			[335.7, 486.2]
	$\lambda_{\texttt{risk}}$		230.06
			[201.3, 265.2]
	obs	9600	9600
	LL	-4837.01	-4797.82

* Confidence intervals were obtained via a bootstrap procedure. In each of 10,000 iterations, we drew a random sample of subjects, with replacement, and then estimated the model's parameters. We then take the 2.5 and 97.5 percentiles from the distribution of estimates as our confidence interval. Note that we draw our random sample at the level of the subject, taking each selected subject's 100 observations.

We first focus on the probability weighting model results in Table 6(a). The implicit annual interest rate used by subjects is over 80% and the coefficient of relative risk aversion

[36] We include all data, even those subjects who were dropped in the reduced form switch point analysis because of multiple switch points. Since the empirical model here assumes that subjects may make stochastic errors, we feel that it is inappropriate to drop these subjects (who may have been making errors) from the analysis. Whether or not they are included in the estimation, the results are qualitatively similar.

is 0.514, suggesting substantial impatience and risk aversion. However, since our empirical model explicitly allows for non-linear probability weighting, which we find to be highly significant, the observed behavior of subjects appears less risk averse than the estimate of ρ would suggest. Additionally, note that because we allow for non-linear probability weighting, our estimates of risk and time preferences are not directly comparable to those found in the existing the literature (e.g., Andersen et al. (2008), Andreoni and Sprenger (2012)). We do note that estimates of the implicit annual interest rate used by subjects vary greatly in both lab and field experiments. The previous experimental literature provides a large range of this estimate (see Frederick, Loewenstein, and O'Donoghue (2002)). For example, Gately (1980) estimates the discount rate for refrigerator buyers varying 45-300%, and the estimates of Benhabib et al. (2010) range from 50 to 9363%. In this regard, our estimates are in line with the previous work. In Appendix C.2 we analyze restricted models, such as imposing risk neutrality and/or linear probability weights, which facilitate comparison with the literature. Since such a comparison is not our primary concern, we refer the interested reader there for more discussion.

We estimate α, the probability weighting parameter, to be 0.752. The upper bound of the 95% confidence interval of our estimate is only 0.810, indicating that subjects have substantial non-linear probability weighting which is consistent with the literature (e.g. Jullien and Salanié (2000), Wu and Gonzalez (1996), Stott (2006), Snowberg and Wolfers (2010)).[37] To facilitate interpretation of this parameter, note that $\alpha = 0.752$ implies that a decision maker acts as though he perceives a 10 percent probability as being 15.4 percent and a 1 percent probability as being 4.3 percent.[38] The net result is that subjects will appear significantly less risk averse for gambles involving small probabilities than would be suggested by the estimated risk parameter, ρ, by itself.

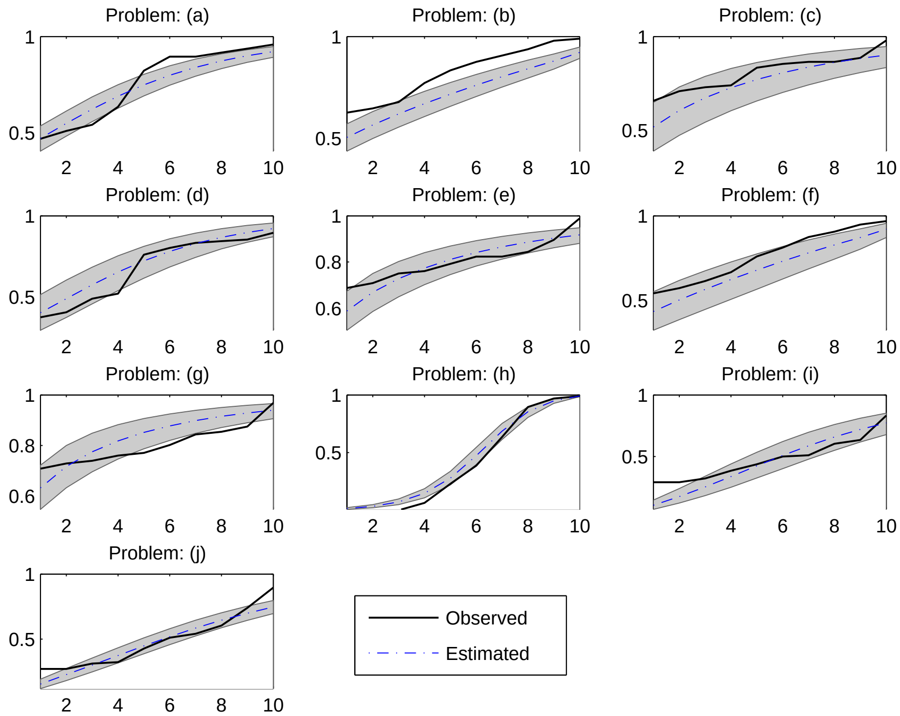
Turning now to the preference for skewness model in Table 6(b), we see that ϕ is significantly positive indicating that subjects have a preference for positive skewness. On the other hand, the positive and significant value of τ indicates that subjects' utility is decreasing as the variance of a gamble increases. As was the case with the probability weighting model, our estimate of the interest rate is the least precise. Indeed, as column (1) suggests we cannot even conclude that $r > 0$ at the 5% level.

Although the models are non-nested, because they have the same number of parameters, a comparison of log-likelihoods is a valid first criterion for selecting among them. On these

[37] It also implies that such decision makers will engage in seemingly risk-seeking behavior for gambles involving low probabilities. For example, such a decision maker would prefer the lottery $[(510, 10); (0.02, 0.98)]$ (the expected value of which is \$20) to \$20 for sure.

[38] To see this, plug in probability values 0.1 and 0.01 into the probability weighting function, $w(p) = e^{-(-\ln p)^{\alpha}}$, with $\alpha = 0.752$.

Figure 1: Predicted vs. Empirical Choice Frequencies



On the horizontal axis, for each problem (a)–(j), is the question number. The vertical axis is the frequency with which Option B is chosen. The solid line denotes the observed empirical frequency, while the dashed line is the prediction. The shaded region represents the 95% confidence band, generated via 10,000 bootstrap replications.

grounds, we would select the probability weighting model. This conclusion is further reinforced by the Vuong (1989) test, which also strongly favors the probability weighting model ($p \ll 0.01$ for both the one-λ and three-λ versions of the models). Finally, if we compare the sum of absolute deviation of the predicted versus empirical frequency that subjects will choose option B (the delayed/risky option) for each of the 100 questions, we also see that the probability weighting model is preferred (5.83 vs 6.13). Given these findings and in the interest of parsimony, henceforth, we focus our attention on the probability weighting model.

In Figure 1 we plot the predicted and empirical frequency with which subjects choose option B for each of the questions faced by the subjects in our experiment based on (1) from the probability weighting model. The shaded region represents the 95% confidence interval of the prediction based on 10,000 bootstrap replications. As can be seen, with the exception of Problem (b), where our model under-predicts the frequency of payment deferral, the empirical choice frequencies are almost always contained within the 95% confidence bands.

4.2.2 Structural Results Based on Observable Characteristics

In this section we explore demographic differences in estimated parameters. In particular, we consider how parameters vary along the three dimensions explored above: (a) self-reported lottery players vs. self-reported lottery abstainers; (b) male vs. female; and (c) those with a combined balance in their savings and checking accounts of more or less than \$1000. The results are presented in Table 7. The top row of the table shows estimates of the parameters for the reference group, male non-lottery players with less than \$1,000 in savings. For this reference group, we estimate $\alpha = 0.760$, $\rho = 0.480$ and $r = 1.328$. The model restricts the rationality parameters to be the same for all individuals, but allows for different rationality parameters for the different problem types.

Table 7: Structural Estimation Results Based on Observable Characteristics

Parameter	$\lambda_{\texttt{time}}$	$\lambda_{\texttt{PLS}}$	$\lambda_{\texttt{risk}}$	α	ρ	r
constant	1.591***	1.718***	1.452***	0.760***	0.480***	1.328***
female				0.059***	0.029	−0.109
lottery				−0.038**	−0.005	0.440***
savings > \$1000				0.012	0.013	−1.018***
		LL	-4619.95		N	9600

** significant at 5% level; *** significant at 1% level

The subsequent rows of the table present estimates of how α, ρ and r vary with gender, lottery play, and savings amount. We find no significant difference in risk aversion or discount rates between men and women. However, we estimate that the probability weighting parameter α is 0.059 higher for women than for men. This difference is statistically significant at the 1-percent level, and implies that men overweight small probabilities more than women. This difference in probability weighting between men and women is consistent with the finding that men had stronger relative preferences for PLS than women. It suggests that the reason why men responded more strongly than women to PLS may be that they more strongly overweight the chance of winning a large prize when the probability of winning is small.

The next row shows how the estimated structural parameters vary between self-reported lottery players and non-players. We estimate that α for lottery players is 0.038 smaller than for non-players. This difference is statistically significant at the 5-percent level and implies that lottery players overweight small probabilities more than non-players. Interestingly, and perhaps surprisingly, we find no difference in risk-aversion between lottery players and non-players. We also find that lottery players are more impatient than non-players. The degree of impatience is unlikely to explain preferences for PLS relative to standard interest savings accounts, since, in our experiment, both PLS and standard interest accounts pay interest equally far in the future. With this in mind, the structural estimates appear to suggest that lottery players have strong preferences for PLS because of their propensity to overweight small probabilities.

The final row of Table 7 shows estimates of how the structural parameters vary for subjects with more than \$1,000 in combined savings, relative to those with less. We find no difference in probability weighting or risk aversion between these two groups. Not surprisingly, we find that those with larger account balances are more future oriented.

4.3 Incorporating Unobserved Heterogeneity

As we have noted, there appears to be substantial heterogeneity of behavior across subjects. Some of this heterogeneity can be explained by certain observable characteristics such as gender, savings account balances and whether or not they play the lottery. We now investigate the extent to which unobserved heterogeneity also explains patterns in our data. Here, rather than assuming that the same parameter vector, (θ, λ), holds for all decision makers, we assume that the parameter vector for subject i is drawn from some distribution, $G(\Theta, \Lambda)$. Specifically, for $\xi_j \in \{\alpha, r, \rho, \lambda\}$, let $X_{\xi_j} \sim N(\xi_j^0, \sigma_{\xi_j}^2)$ denote a normal random variable. Since $\lambda, r \geq 0$, we have that λ is distributed according to e^{X_λ}, and similarly for the interest rate, r. The probability weighting parameter α is distributed according to $e^{X_\alpha}/(1 + e^{X_\alpha})$ to ensure that it is between 0 and 1. Finally, since ρ is unrestricted, it is simply distributed according to X_ρ. For tractability, we assume independence across the components of (Θ, Λ). That is X_{ξ_j} and X_{ξ_k} are statistically independent for all j and k.

As suggested by Train (2003), we estimate the model by simulated maximum likelihood. We construct the simulated likelihood function as follows. For each person i, let $c_{i,t} \in \{\ell_a^t, \ell_b^t\}$ denote the choice of lottery for person i's t^{th} decision. Next, draw a parameter vector (θ^m, λ^m) from the distribution G and compute

$$L_{i,m}(\theta^m, \lambda^m) = \prod_{t=1}^{T} \left[\frac{e^{\lambda^m U(c_{i,t};\theta^m)}}{e^{\lambda^m U(\ell_a^t;\theta^m)} + e^{\lambda^m U(\ell_b^t;\theta^m)}} \right].$$

We then take the average of $L_{i,m}$ over a large number (M) of random parameter draws from G to obtain:

$$\bar{L}_i = \frac{1}{M} \sum_{i=1}^{M} L_{i,m}(\theta^m, \lambda^m).$$

Table 8: Structural Estimation Results: Unobserved Heterogeneity

Parameter		Mean	Variance
Risk Pref.	ρ	0.528	0.042
		[0.38, 0.61]	[0.03, 0.15]
Prob Wgt.	α	0.730	1.256
		[0.68, 0.82]	[0.72, 2.71]
Int. Rate	r	0.589	2.491
		[0.41, 1.09]	[1.26, 3.89]
Rationality	λ	6.270	0.382
		[4.62, 8.91]	[0.26, 1.22]
	obs	9600	
	LL	-2343.32	

Finally, the simulated log likelihood is given by:

$$SLL = \sum_{i=1}^{N} \log(\bar{L}_i).$$

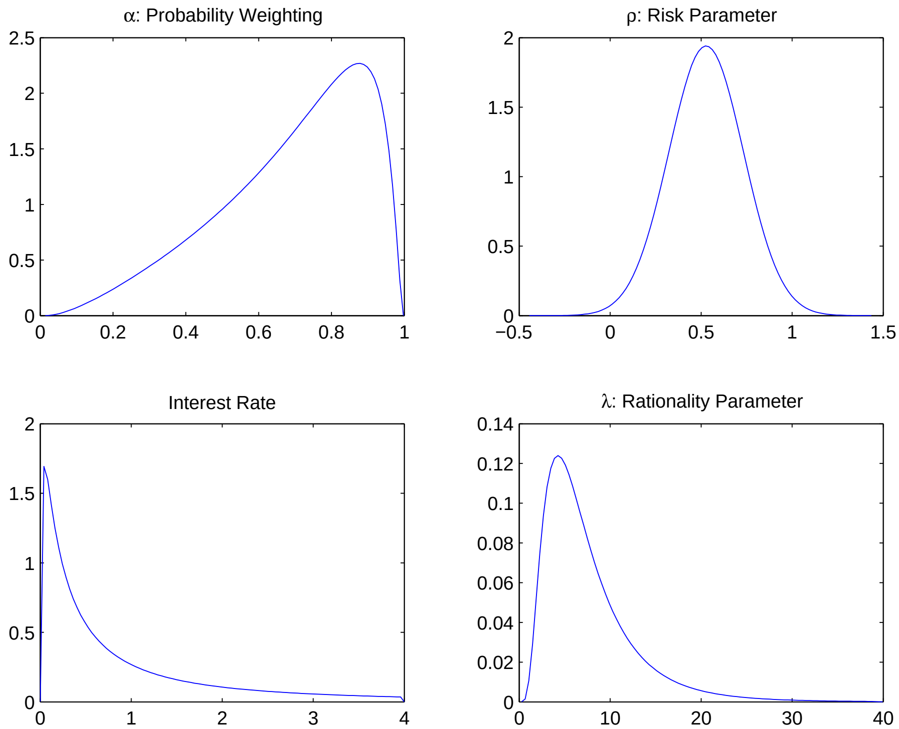
We then search for the parameter vector $(\hat{\alpha}, \hat{\rho}, \hat{r}, \hat{\lambda}, \hat{\sigma}^2_\alpha, \hat{\sigma}^2_\rho, \hat{\sigma}^2_r, \hat{\sigma}^2_\lambda)$ that maximizes the simulated log likelihood.

The parameter estimates, with bootstrapped confidence intervals in brackets, are on display in Table 8. To facilitate the comparison with our pooled estimation results reported in Table 6(a), the column labeled "Mean" reports the mean of the estimated distribution for the parameter of interest.[39] Particularly for the risk and probability weighting coefficients, the estimated means of the distribution correspond very closely to the pooled estimates. Note also that all the estimated means are within the 95% confidence interval of the pooled estimates. Although it is hard to interpret the "Variance" column precisely, the main takeaway is that the variance is always significantly positive; that is, for each parameter, there is substantial unobserved heterogeneity.

To get a sense of what these parameter estimates imply in terms of the actual parameters of interest and the extent of unobserved heterogeneity, in Figure 2, we plot kernel density estimates of the distributions for α, ρ, r (truncated at $r = 4$) and λ (truncated at $\lambda = 40$). For the probability weighting parameter, α, while the average value is 0.730, the distribution is not symmetric, with a fairly large proportion with a more mild form of probability weighting. Similarly, the distributions for the interest rate, r and the rationality parameter, λ, are

[39]To be more precise, we estimate the mean and variance of a normal distribution and then apply a transformation so that the actual variable of interest lies in the appropriate domain. For example, for the probability weighting parameter, we estimated ξ^0_α and σ^2_α. The number reported in the table is then $0.730 = \exp(\xi^0_\alpha)/(1 + \exp(\xi^0_\alpha))$, where ξ^0_α is the actual parameter estimated.

Figure 2: Kernel Density Estimates of Preference Parameter Distributions

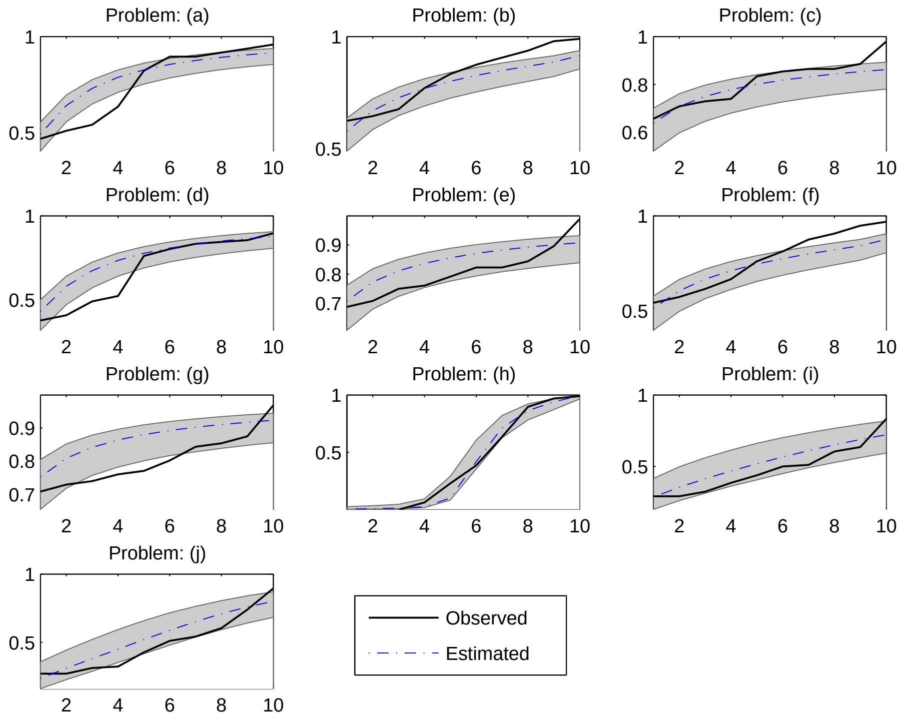


right-skewed indicating some highly impatient subjects, as well as some who approach full rationality. Finally, for the coefficient of relative risk aversion, the distribution is symmetric about the mean of 0.528 and the variance is fairly small, with a very small proportion of subjects being risk seeking and a similarly small proportion of subjects have coefficients of relative risk aversion greater than 1.

At first glance, it appears that the four additional parameters introduced in the model with unobserved heterogeneity substantially improves the explanatory power of the model: the log-likelihood improves by 50% (vs. the 2.1% improvement for observed heterogeneity). In fact, this is somewhat deceptive. Because the distribution of parameters is non-degenerate, individual-level predictions are sharper; that is, for a given draw from $G(\Theta, \Lambda)$, the predicted probability of choosing the risky/delayed option is closer to 0 or 1. However, when averaging over the type distribution, the average probability of choosing the risky/delayed option is no more accurate at explaining the observed behavior at the aggregate level than is our earlier model without unobserved heterogeneity. This can be seen in Figure 3, which replicates 1 but for the case of unobserved heterogeneity.[40]

[40]We will see this later when we try to quantify the effects of offering PLS on savings. Specifically, the predicted response based on our baseline model is virtually identical to the median response for our model of unobserved heterogeneity.

Figure 3: Unobserved Heterogeneity: Average Predicted vs. Empirical Choice Frequencies



On the horizontal axis, for each problem (a)–(j), is the question number. The vertical axis is the frequency with which Option B is chosen. The solid line denotes the observed empirical frequency, while the dashed line is the prediction. The shaded region represents the 95% confidence band, generated via 10,000 bootstrap replications.

5 Quantifying The Effect of PLS on Savings

5.1 Theoretical Background

In this section we first show theoretically that if subjects have non-linear probability weighting, then introducing a PLS device will increase savings. We then conduct simulation exercises using the structural parameter estimates presented above to examine the conditions under which PLS products are more desirable than a standard interest bearing asset. Throughout we assume that the decision maker chooses the alternative yielding higher utility. We begin by considering a situation in which the decision maker has $\$\pi$ and can choose one of two options: (i) invest in a savings account that pays interest rate i at time t or (ii) invest in a PLS device that pays interest $\frac{i}{p} > i$ at time t with probability p and pays no interest with probability $1-p$ — that is, the expected cost to the bank is the same under both scenarios.[41]

[41] A similar analysis can be done by designing a PLS that makes the decision maker indifferent and the bank better off. As can be seen in the proof of Proposition 1, the main idea is to have non-linear probabilities for the decision maker. One can also repeat a similar exercise with a PLS design that pays some small interest when the investor does not win the big prize. We chose not to perform that exercise here to stay close to our experimental design.

Then the utility of saving in the standard interest bearing option is

$$U^{\mathtt{int}} = e^{-rt}\frac{[(1+i)\pi]^{1-\rho} - 1}{1-\rho},$$

while the utility of saving in the PLS device is

$$U^{\mathtt{pls}} = e^{-rt}\frac{w(p)\,[(1+i/p)\pi]^{1-\rho} + (1-w(p))\,[\pi]^{1-\rho} - 1}{1-\rho}.$$

Next, we show that one can design a prize-linked saving option such that the utility of the PLS option is higher than the utility of the sure interest paying option and both of them cost the same in expectation.

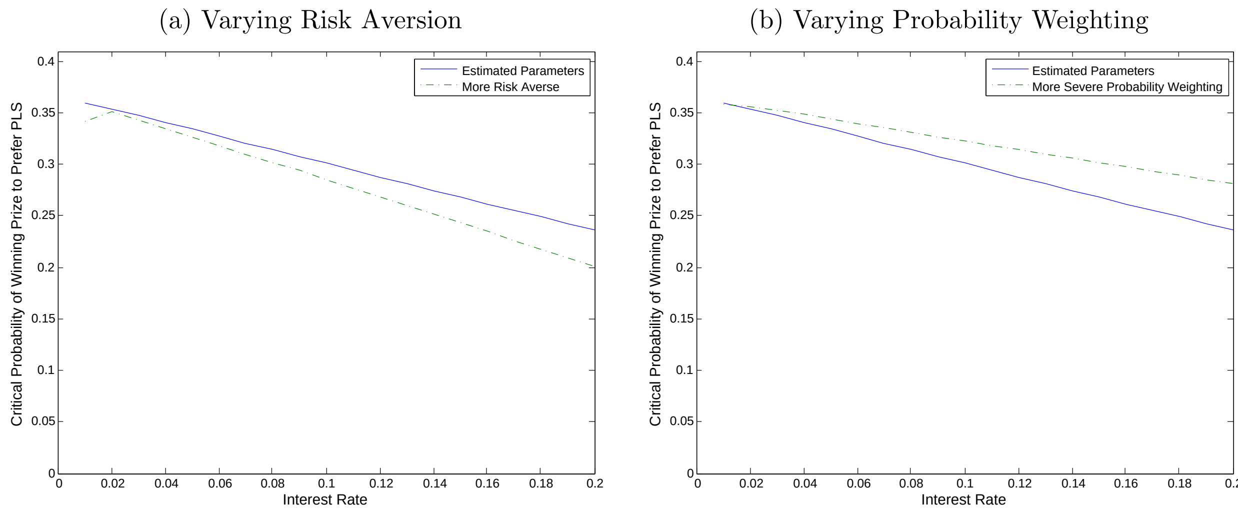
Proposition 1. *For any $\alpha < 1$ there exists a $p^*(i, \rho, \alpha) \in (0, 1)$ such that for all $p < p^*(i, \rho, \alpha)$, $U^{pls} > U^{int}$.*

Proof. See Appendix D. □

Technically, the result above may require the combination of an extremely small probability of winning paired (by construction) with an extremely large prize. However, given the parameter estimates that we reported earlier, PLS dominates standard interest bearing accounts even for "reasonable" probabilities and prize sizes. For example, in Figure 4, we plot the critical probability of winning the prize as a function of the interest rate.[42] In both panels, the solid line is generated using our parameter estimates from (2) of Table 6(a). The $-.-$ line in panel (a) takes the same parameter estimates but substitutes a higher value of the coefficient of relative risk aversion (i.e., an increase in ρ from the estimated value of 0.497 to 0.597); similarly, the $-.-$ line in panel (b) considers more severe form of probability weighting (i.e., a reduction in α from the estimated value of 0.768 to 0.668). As can be seen, the critical value of the probability of winning is never below 0.2. Panel (a) shows that if, holding all other variables constant at our parameter estimates, if we make a subject more risk averse, then to get her to choose the PLS option, rather than the standard interest bearing option, we will have to offer him a smaller probability of winning a larger prize. This is because the distortion in perceived probabilities is relatively larger at smaller probabilities, making her more willing to choose the risky option. Panel (b) shows if, holding all other variables constant at our parameter estimates, we make a subject have more severe probability weighting, then to get her to choose the PLS option over the standard interest bearing option, it is enough to offer a smaller prize with a higher probability of winning.

[42]Observe that if the standard interest rate is i, then the PLS device offers an interest rate of i/p with probability p.

Figure 4: Critical Value of Probability of Winning Prize to Prefer PLS Over Standard Interest Bearing Option



Note: In Panel (a), the solid line denotes, at the estimated parameters of our structural model, the critical probability that would make a subject just indifferent between a PLS device which returns a prize with probability p and an interest only account that pays interest rate i. The dash-dotted line shows how this critical value changes if the subject is made *more risk averse*. Not surprisingly, the critical value goes down, which means that a smaller probability of winning a larger prize is required to induce the subject to save with PLS. In Panel (b), we repeat the same exercise but consider the effect of a change from the probability weighting that we estimate to a more severe form of probability weighting. In this case, we see that the critical probability increases. That is, the more severe the probability weighting, the smaller the PLS prize can be to induce the subject to save with a PLS device. In all cases, the expected return to PLS is equal to the interest rate.

This is also intuitive since, because of the increase in the severity of probability weighting, the decision maker will be more optimistic about winning the prize.

Turn now to a situation in which a decision maker faces a portfolio choice problem. Specifically, she has $\$\pi$ which can be allocated to current consumption, x_c, or future consumption, x_f. Additionally, assume that there are two types of investments: interest only and PLS. Specifically, if $x_{f,i}$ is invested in the interest only option, then in period t, the DM will receive $(1+i)x_{f,i}$. On the other hand, if $x_{f,p}$ is invested in the PLS device, then she will receive $(1+i/p)x_{f,p}$ with probability p at time t and $x_{f,p}$ with probability $1-p$, also at time t. The decision maker's problem is then to choose $\{x_c, x_{f,i}, x_{f,p}\}$ to maximize:

$$\frac{x_c^{1-\rho}-1}{1-\rho}+e^{-rt}\frac{w(p)\left[x_{f,i}(1+i)+x_{f,p}(1+i/p)\right]^{1-\rho}+(1-w(p))\left[x_{f,i}(1+i)+x_{f,p}\right]^{1-\rho}-1}{1-\rho}$$

subject to $x_c + x_{f,i} + x_{f,p} = \pi$.

Assuming $\rho > 0$, it is possible to show that, at the optimal solution, $x_c \in (0, \pi)$ and that:

$$(x_{f,i}, x_{f,p}) = \begin{cases} \left(\frac{\pi}{[e^{-rt}(1+i)^{1-\rho}]^{-1/\rho}+1}, 0\right), & \text{if } (A-1)(1+i) > 0 \\ \left(0, \frac{\pi}{[e^{-rt}(w(p)(1+i/p)^{1-\rho}+1-w(p))]^{-1/\rho}+1}\right) & \text{if } A(1+i/p) < 1 \ \& \ (A-1)(1+i) < 0 \\ (x_{f,i}, x_{f,p}) > 0, & \text{otherwise} \end{cases}$$

where $A = \left(\frac{(1-w(p))}{w(p)(1/p-1)}\right)^{1/\rho}$.

Notice also that if the PLS option is not available, then the decision maker will always allocate $x_{f,i}^{INT} = \frac{\pi}{[e^{-rt}(1+i)^{1-\rho}]^{-1/\rho}+1}$ to future consumption.

Beyond this, we also have the following result:

Proposition 2. *For all $\alpha \in (0,1)$ and all $\rho \in (0,1)$, there exists $\hat{p} < 1$ such that for $p < \hat{p}$, the decision maker allocates all future consumption to the PLS device and that the amount of money devoted to future consumption, $x_{f,p}^{PLS}$ is larger than the amount devoted, $x_{f,i}^{INT}$ when only interest-only savings are available.*

Proof. See Appendix D. □

That is, there is a probability of winning small enough (with prize accordingly large) such that a moderately risk averse decision maker (i.e., $\rho \in (0,1)$) who exhibits non-linear probability weighting (i.e., $\alpha \in (0,1)$) will allocate all future consumption to the PLS option and, moreover, this amount is larger than the amount she would allocate if she only had access to a standard interest-bearing account.

Propositions 1 and 2 conclude that it is possible to design the PLS option to increase savings with no additional cost to the offering institutions. Both results are driven by investors who have non-linear probability weighting functions. In Appendix E, we demonstrate that it is not possible to replicate these results for a decision maker who has a preference for skewness as in Mitton and Vorkink (2007). The basic intuition is that for the PLS products we consider, the variance of the lottery (which reduces utility) increases faster than does the skewness (which increases utility) as the probability of winning the prize decreases (and the size of the prize increases).

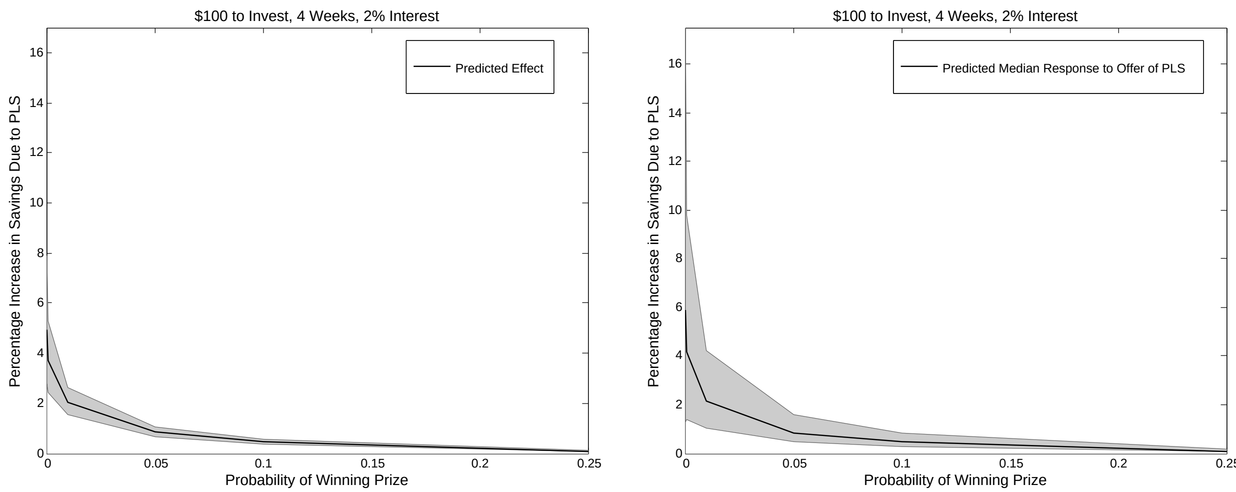
5.2 Quantifying the Effect of PLS: Simulation Analysis

In this section we ask whether decision makers, with the parameters estimated from our structural model of non-linear probability weighting, could be induced to increase their savings by making prize-linked savings devices available. Before delving into to a larger

Figure 5: The Impact of PLS on Savings as a Function of Win Probability: Pooled Estimates vs. Median Response With Unobserved Heterogeneity

(a) Pooled Estimate

(b) Unobserved Heterogeneity

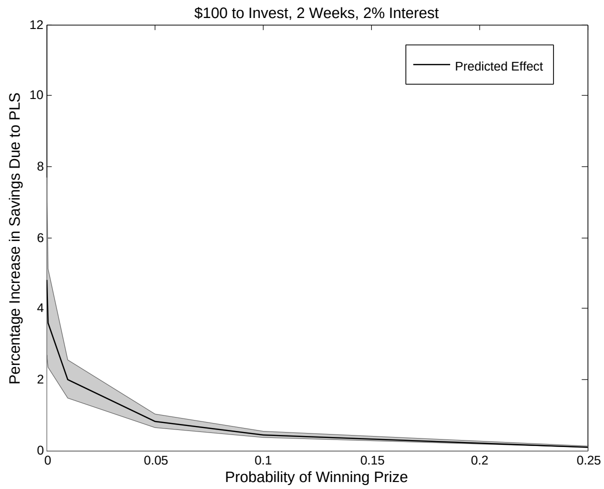


analysis, we first show that our pooled estimates from Table 6(a) lead to predictions very close to the predicted median response in our model of unobserved heterogeneity from Table 8. To this end consider Figure 5 which shows the percentage increase in savings when a PLS device is introduced as an alternative to a standard interest bearing account that pays 2% interest in 4 weeks. Panel (a) considers the pooled estimates, while panel (b) shows the median response in our model of unobserved heterogeneity. In both cases, the shaded region represents the 95% confidence band based on 10,000 bootstrap replications. As can be seen, the predicted effect in both cases is almost exactly the same, and it is significantly positive. The main difference is that the 95% confidence band is somewhat wider for the predicted median response. We can draw two conclusions from this. First, our main predictions about the effect of PLS on savings are robust to the presence of unobserved heterogeneity. Second, a substantial proportion of people would increase savings by more than 4% with the introduction of a PLS device that paid a prize of $200 with probability 0.01% for every dollar invested in PLS.

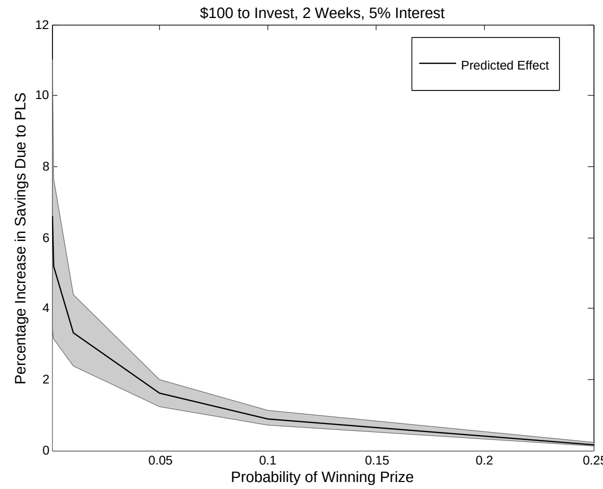
In Figure 6 we show the impact on savings of offering a PLS savings device as we vary the probability of winning the prize. In all cases, the decision maker is assumed to have $100 to allocate to either present or future consumption. We consider 2 different time periods — 2 and 4 weeks — and two different interest rates — 2% and 5%. The solid lines represent the predicted effect based on our pooled estimates, and the shaded area is the 95% confidence region. As can be seen in the figure, for a 0.01% chance of winning — and a corresponding increase in the prize to keep expected value fixed — the offer of PLS increases savings by

Figure 6: The Impact of PLS on Savings: Changes in Interest Rate and Payment Delay

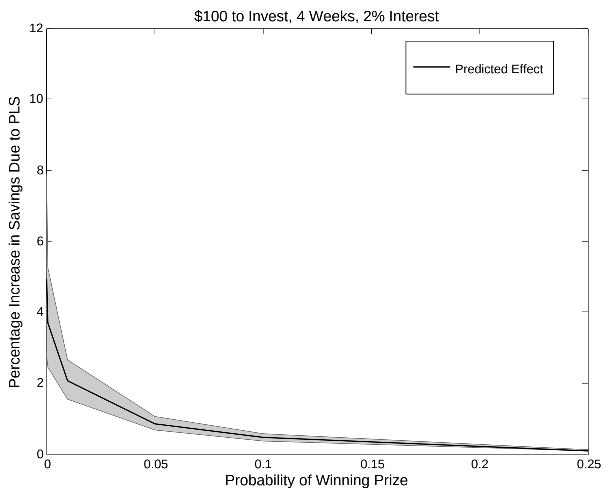
(a) $t = 2$ weeks; $i = 2\%$; saving w/o PLS = 48.9



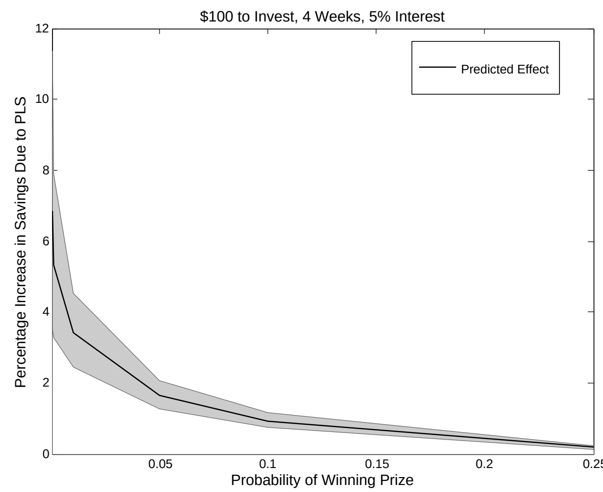
(b) $t = 2$ weeks; $i = 5\%$; saving w/o PLS = 49.6



(c) $t = 4$ weeks; $i = 2\%$; saving w/o PLS = 47.4



(d) $t = 4$ weeks; $i = 5\%$; saving w/o PLS = 48.0

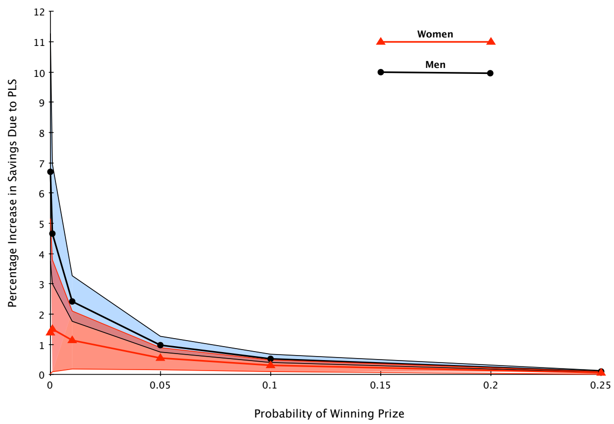


between 4.8 and 9.2%. The response to PLS appears to increase with the time horizon and the interest rate of the traditional interest-bearing account. To give a sense of the magnitudes, in the plot captions we also report the amount that the decision maker would allocate to future consumption in the absence of PLS. For example, the 4.8% effect due to PLS in panel (a) increases savings from \$48.9 to \$51.2.

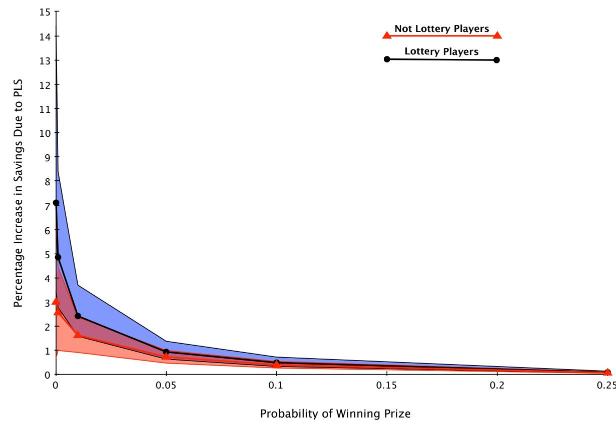
Finally, we turn briefly to the differential response to the introduction of PLS by certain observable characteristics. In the interest of parsimony we focus only on gender and whether or not one plays the lottery. These were the two observable characteristics that our descriptive analysis found to yield the most significant differences. The results are displayed in Figure 7, with panel (a) showing the results for gender and panel (b) showing the results

Figure 7: The Impact of PLS on Savings: Observable Characteristics

(a) Gender: $t = 4$ weeks; $i = 2\%$



(b) Lottery: $t = 4$ weeks; $i = 2\%$



These plots show the 95% confidence bands for the differential response to PLS by gender (panel (a)) or by lottery playing status (panel (b)). It is important to note that despite the fact that the 95% confidence bands overlap, for both comparisons, a two-sample $t-$test strongly rejects the null hypothesis that the response to PLS is the same.

for whether or not subjects play the lottery. The shaded regions represent the 95% confidence bands. Consider panel (a). First the effect on savings is small and barely significant at the 5% level. Second, although the 95% confidence bands for men and women overlap a two-sample $t-$test of the underlying data strongly rejects (at $p \ll 0.01$) that the response to PLS is the same for all probabilities of winning the prize. Consider next panel (b). We again observe that the 95% confidence bands overlap for those who play the lottery and those who do not. However, as was the case with gender, a two-sample $t-$test of the underlying data rejects the hypothesis that the response to PLS is the same for those who do and do not play the lottery.

6 Conclusion

This paper has provided laboratory evidence on individual choices over earlier consumption versus later consumption (savings) as a function of whether the decision-maker is offered a standard interest bearing account or a prize-linked savings account. The data from the experiment demonstrate clearly that individuals are enticed to save at a higher rate – for a given expected return – if they are presented with a prize-linked savings choice. Ours is the first paper that provides evidence that PLS products are more effective at inducing savings as compared to a standard interest bearing account.

This finding should be of immediate interest to the research and policy community interested in innovations in the savings sphere. The existing evidence about PLS products coming from real world offerings of such products speaks only to the take-up of the product itself, and does not provide any guidance about whether the take-up of PLS reflects new savings or displaced savings from other potential assets. Establishing the effectiveness of PLS products at encouraging new savings in a laboratory setting is an important first step in providing insight into whether PLS products might encourage new saving, as opposed to displaced saving. Follow-up work should consider embedding PLS in a more direct portfolio-choice model as in our simulation exercise in order to gain further insight into the welfare impact of introducing PLS (see Atalay et al. (Forthcoming) for work in this direction).[43] We also hope to have an opportunity to pursue follow up work in a field experiment setting. A subset of the authors of this article have been pursuing such opportunities for nearly a decade, but idiosyncratic implementation barriers have precluded that from taking place. Legal barriers to the offering of PLS products in the U.S. are becoming less binding, which hopefully will lead to fruitful opportunities to offer such products as part of a research demonstration. We leave it as an open question whether PLS are substitutes or compliments to state lotteries. In some applications, PLS has been withdrawn from the market because it turned out to be substitute for state lotteries (South Africa) but they coexist with lotteries in many countries.

The paper has further provided structural estimates of the underlying decision parameters of interest. Using recently developed techniques, we jointly elicited parameters governing time preference, risk preference, and probability weighting. Not surprisingly, we find that probability weighting is related to the appeal of PLS products. This raises interesting questions about social welfare. Should we promote products in which the appeal is generated by misrepresentations of probabilities in the decision-maker's optimization problem? It also raises questions about long term effectiveness – in a repeated context, will consumers eventually adjust their probability weights to remove such "bias" from their decision making? The paper does not propose to answer these interesting questions.

An additional limitation of the paper is that the experiment was not designed to isolate various explanations for the appeal of PLS—though our results do suggest that non-linear probability weighting provides a better explanation that preferences for skewness. An additional possibility which we do not consider in this paper is non-stationary discount factors, as in Ahlbrecht and Weber (1997b) and Stevenson (1992). More generally, while our paper and others (e.g., Epper and Fehr-Duda (2013)) have made some progress, studying the interaction between risk and time preferences is an important area for future research.

[43]Since an individual's future consumption opportunities are smaller under PLS than under an equivalent interest-only account if she does not win the prize, if all PLS savings simply displace traditional savings accounts, then PLS need not be welfare improving. However, if PLS encourages new savings, then, from the starting point of inadequate initial savings highlighted in the introduction, PLS is likely to be welfare improving—even if future consumption possibilities are lower than had the individual chosen to put the new savings in a traditional account.

References

Abdellaoui, M. (2000). Parameter-free elicitation of utilities and probability weighting functions. *Management Science 47*(11), 1497–1512.

Ahlbrecht, M. and M. Weber (1997a). An empirical study on intertemporal decision making under risk. *Management Science 43*(6), 813–826.

Ahlbrecht, M. and M. Weber (1997b). Preference for gradual resolution of uncertainty. *Theory and Decision 43*, 167–185.

Andersen, S., G. W. Harrison, M. Lau, and E. E. Rutström (2011a). Intertemporal utility and correlation aversion. Unpublished.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2008). Eliciting risk and time preferences. *Econometrica 76*(3), 583–618.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2011b). Discounting behavior: A reconsideration. Unpublished.

Anderson, L. R. and S. L. Stafford (2009). Individual decision making experiments with risk and intertemporal choice. *Journal of Risk and Uncertainty 38*(1), 51–72.

Andreoni, J. and C. Sprenger (2012). Estimating time preferences from convex budget sets. *American Economic Review 107*(7), 3333–3356.

Atalay, K., F. Bakhtiar, S. Cheung, and R. Slonim (Forthcoming). Savings and prize-linked savings accounts. *Journal of Economic Behavior & Organization*.

Azriele, Y., C. P. Chambers, and P. J. Healy (2012). Incentives in experiments: A theoretical analysis. Working Paper.

Barberis, N. and M. Huang (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review 98*(5), 2066–2100.

Barseghyan, L., F. Molinari, T. O'Donoghue, and J. C. Teitelbaum (Forthcoming). The nature of risk preferences: Evidence from insurance choices. *American Economic Review*.

Benhabib, J., A. Bisin, and A. Schotter (2010). Present-bias, quasi-hyperbolic discounting, and fixed costs. *Games and Economic Behavior 69*, 205–23.

Booij, A. S., B. M. S. van Praag, and G. van de Kuilen (2010). A parametric analysis of prospect theory's functionals for the general population. *Theory and Decision 68*(1-2), 115–148.

Bruhin, A., H. Fehr-Duda, and T. Epper (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica 78*(4), 1375–1412.

Brunnermeier, M. K. and J. A. Parker (2005). Optimal expectations. *American Economic Review 95*(4), 1092–1118.

Chetty, R., J. Friedman, S. Leth-Petersen, T. Nielsen, and T. Olsen (2012). Active vs. passive decisions and crowd-out in retirement savings accounts: Evidence from denmark. NBER Working Paper 18565.

Chew, S. H. and J. L. Ho (1994). Hope: An empirical study of attitude toward the timing of uncertainty resolution. *Journal of Risk and Uncertainty 8*(3), 267–288.

Coble, K. H. and J. L. Lusk (2010). At the nexus of risk and time preferences: An experimental investigation. *Journal of Risk and Uncertainty 41*, 67–79.

Conlisk, J. (1993). The utility of gambling. *Journal of Risk and Uncertainty 6*(3), 255–275.

Croson, R. and U. Gneezy (2009). Gender differences in preferences. *Journal of Economic Literature 47*(2), 1–27.

Cubitt, R., C. Starmer, and R. Sugden (1998). On the validity of the random lottery incentive scheme. *Experimental Economics 1*(2), 115–131.

Epper, T. and H. Fehr-Duda (2013). The missing link: Unifying risk taking and time discounting. University of Zurich Working Paper No. 96.

Fehr-Duda, H., M. de Gennaro, and R. Schubert (2006). Gender, financial risk and probability weights. *Theory and Decision 60*(2-3), 283–313.

Fischbacher, U. (2007, June). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10*(2), 171–178.

Frederick, S., G. Loewenstein, and T. O'Donoghue (2002). Time discounting and time prefrence: A critical review. *Journal of Economic Literature XL*, 351–401.

Gately, D. (1980). Individual discount rates and the purchase and utilization of energy-using durables: Comment. *Bell Journal of Economcis 11*(1), 373–374.

Gonzalez, R. and G. Wu (1999). On the shape of the probability weighting function. *Cognitive Psychology 38*(1), 129–166.

Guryan, J. and M. Kearney (2008). Gambling at lucky stores: Evidence from state lottery sales. *American Economic Review 98*(1), 458–473.

Harrison, G. W. and E. E. Rutström (2008). Risk aversion in the laboratory. In J. C. Cox and G. W. Harrison (Eds.), *Risk Aversion in Experiments, Research in Experimental Economics*, Volume 12. Bingley, U.K.: Emerald.

Harrison, G. W. and J. T. Swarthout (2014). Experimental payment protocols and the bipolar behaviorist. *Theory and Decision 77*(3), 423–438.

Holt, C. A. and S. K. Laury (2002). Risk aversion and incentive effects. *American Economic Review 92*(5), 1644–1655.

Hsu, M., I. Krajbich, C. Zhao, and C. F. Camerer (2009). Neural response to reward anticipation under risk is nonlinear in probabilities. *Journal of Neuroscience 29*(7), 2331–2337.

Hu, W.-Y. and J. S. Scott (2007). Behavioral obstacles in the annuity market. *Financial Analsysts Journal 63*(6), 71–82.

Jullien, B. and B. Salanié (2000). The case of racetrack bettors. *Journal of Political Economy 108*(3), 503–530.

Kearney, M. (2005). State lotteries and consumer behavior. *Journal of Public Economics 89*, 2269–2299.

Kearney, M., P. Tufano, J. Guryan, and E. Hurst (2010). Making savers winners: An overview of prize-linked savings products. NBER Working Paper 16433.

Keren, G. and P. Roelofsma (1995). Immediacy and certainty in intertemporal choice. *Organizational Behavior and Human Decision Processes 63*(3), 287–297.

Laury, S. K., M. M. McInnes, and J. T. Swarthout (2012). Avoiding the curves: Direct elicitation of time preferences. *Journal of Risk and Uncertainty 44*(3), 181–217.

Lichtenstein, S., P. Slovic, B. Fischhoff, M. Layman, and B. Combs (1978). Judged frequency of lethal events. *Journal of Experimental Psychology: Human Learning and Memory 4*(6), 551–578.

Luce, R. D. (1959). *Individual Choice Behavior: A Theoretical Analysis.* New York: Wiley.

Lusardi, A., D. J. Schneider, and P. Tufano (2011). Financially fragile households: Evidence and implications. NBER Working Paper 17072.

Madrian, B. and D. F. Shea (2001). The power of suggestion: Inertia in 401(k) participation and savings behavior. *Quarterly Journal of Economics 116*(4), 1149–1187.

Mitton, T. and K. Vorkink (2007). Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies 20*(4), 1255–1288.

Ottaviani, M. and P. N. Sørensen (2009). Surprised by the parimutuel odds? *American Economic Review 99*(5), 2129–2134.

Ottaviani, M. and P. N. Sørensen (2010). Noise, information, and the favorite-longshot bias in parimutuel predictions. *American Economic Journal: Microeconomics 2*(1), 58–85.

Prelec, D. (1998). The probability weighting function. *Econometrica 66*(3), 497–527.

Roger, P. (2011). Testing alternative theories of financial decision making: A survey with lottery bonds. *Journal of Behavioral Finance 12*(4), 219–232.

Snowberg, E. and J. Wolfers (2010). Explaining the favorite-long shot bias: Is it risk-love or misperceptions? *Journal of Political Economy 118*(4), 723–746.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature 38*(2), 332–382.

Stevenson, M. K. (1992). The impact of temporal context and risk on the judged value of future outcomes. *Organizational Behavior and Human Decision Processes 52*(3), 455–491.

Stott, H. (2006). Cumulative prospect theory's functaional menagerie. *Journal of Risk and Uncertainty 32*(2), 101–130.

Sydnor, J. (2010). (over)insuring modest risks. *American Economic Journal: Applied Economics 2*(4), 177–199.

Thaler, R. and S. Benartzi (2004). Save more tomorrow: Using behavioral economics to increase employee saving. *Journal of Political Economy 112*(1), S164–187.

Thaler, R. H. and C. R. Sunstein (2008). *Nudge: Improving Decisions About Health, Wealth, and Happiness.* Yale University Press.

Train, K. E. (2003). *Discrete Choice Methods with Simulation*. Cambridge University Press.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*, 297–323.

Volpp, K. G., L. K. John, A. B. Troxel, L. Norton, J. Fassbender, and G. Loewenstein (2008a). Financial incentive-based approaches for weight loss: A randomized trial. *Journal of the American Medical Association 300*(22), 2631–2637.

Volpp, K. G., L. K. John, A. B. Troxel, L. Norton, J. Fassbender, and G. Loewenstein (2008b). A test of financial incentives to improve warfarin adherence. *BMC Health Services Research 8*(272).

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica 57*(2), 307–333.

Wu, G. and R. Gonzalez (1996). Curvature of the probability weighting function. *Management Science 42*(12), 1676–1690.

Yaari, M. E. (1987). The dual theory of choice under risk. *Econometrica 55*(1), 95–115.

A Instructions

Welcome and thank you for coming to participate in today's experiment. This experiment is funded by the University of Maryland.

This is a two-part study. In the first part, you will face 10 sets of decision questions, which will take less than 1 hour. In the second part, you need to fill out a questionnaire, which will take about 15 minutes. Today, you will receive $7 for showing-up on time and $3 for completing the questionnaire at the end of the experiment. Additionally, you may earn a substantial amount of money in the first part of the experiment. You are required to come back to the lab again to receive those additional earnings.

During the experiment it is important not to talk to any other subjects, surf the web or use your cell phones. So please turn your cell phones off and remember if you have any questions, just raise your hand and we will come by to answer them.

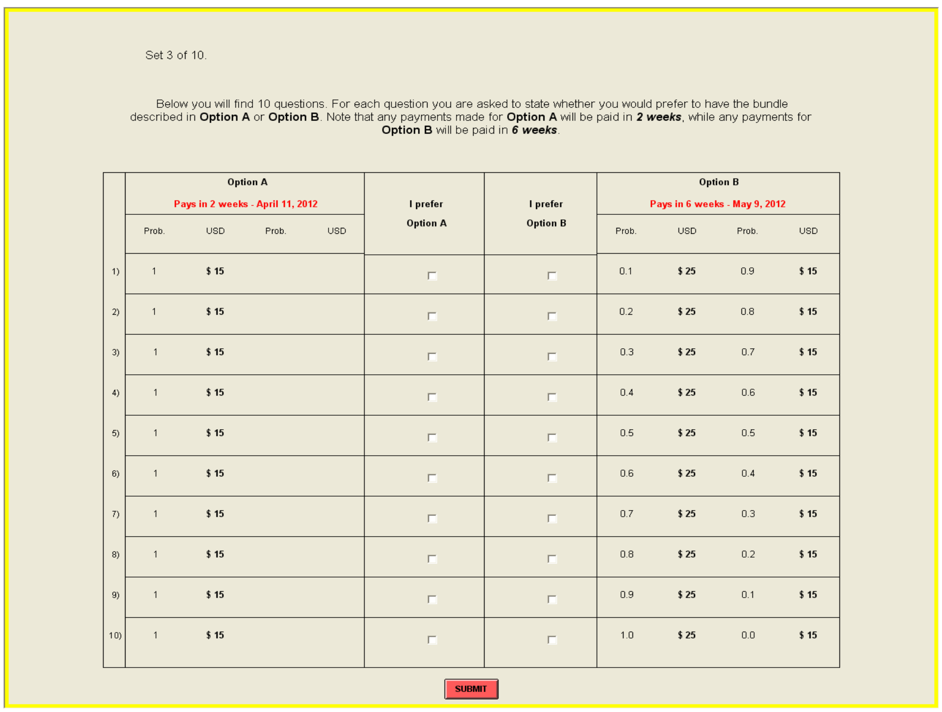
PART I:

In this experiment, you will face 10 sets of decision questions. On each set of decision questions, you will be asked to make 10 decisions. Each decision is a paired choice between "Option A" and "Option B". Therefore, in total, you will make 100 decisions today.

All of the decisions you must make have the same general form. You are choosing between "Option A" and "Option B". Each option is either a lottery with two possible outcomes or a sure payment. Each option also specifies the date that it will be paid.

An example of the screen you will see for a set of decision questions is given in Figure 8. Note that you are asked to make 10 decisions on this screen. As you can see, for each decision, you must choose between Option A and Option B. You may choose Option A for some decisions and Option B for others, and you may change your decisions and make them in any order. Once you have made all of your decisions, press the Submit button and you will be taken to the next, if any decision problem. Note that after you have pressed the submit button, you will no longer be able to change your decisions.

Figure 8: Experimental Interface: Sample Screen



In this example, Option A pays in two weeks, and Option B pays in six weeks. Note that in all the questions, Option A pays $15 for sure; Option B is a lottery that pays either $25 or $15. In Question 1, Option B pays $25 with probability 0.1 and pays $15 with probability 0.9. In Question 2, Option B pays $25 with probability 0.2 and pays $15 with probability 0.8, etc. In Question 10, Option B pays $25 with probability 1 (i.e. $25 for sure).

Notes:

1. Your payment will be based on one of the 100 decisions that will be randomly selected. Here is a ten-sided die that will be used to determine payoffs; the faces are numbered 0 to 9. After you have made all of your choices, and you have completed the questionnaire, the

experimenter will come and let you throw the die twice. The first time you roll the die, will determine which of the 10 sets of decision questions will be used in determining your payoff. The second time you roll the die, will determine which of the decisions will be used to determine your payoff. For example, if you roll a 7 and then a 3, then this means that the 3rd decision on the 7th set of decision questions will be used to determine your payoff. If you roll 0, it will correspond to 10. Since each decision is equally likely to be selected, you should pay equal attention to each question.

2. Depending on your choice, there are two possibilities:

   (a) If the Option you chose in the randomly determined decision question is paying an amount for sure, then you will receive that amount at the specified date for that option.

   (b) If the Option you chose in the randomly determined decision question is a lottery, you will roll the die to determine the outcome of the lottery.

   For example, suppose that that Option pays \$25 with probability 0.1 and \$21 with probability 0.9 in two weeks. In this case, you will roll the ten-sided die one more time. If a 1 comes up, then you will receive \$25 in two weeks, while if a 2, 3, 4, 5, 6, 7, 8, 9, or 0 comes up, then you will receive \$21 in two weeks.

   As a further example, suppose that that Option pays \$215 with probability 0.035 and \$15 with probability 0.965 in five weeks. In this case, you will roll the die three times. These three rolls will correspond to a number from 000 to 999. For example:

   - If you roll a 4, a 6 and an 8 (in that order), then the number corresponds to 468.
   - If you roll 0 three times, then this corresponds to the number 000.
   - If you roll a 7, a 0 and a 2 (in that order), then the number corresponds to 702.

   In this example, if the corresponding number you roll is 001, 002, . . . , or 035, then you will receive \$215 in five weeks. If you roll 036, 037, . . . , 999, or 000, then you will receive \$15 in five weeks.

3. The date at which you will be paid for Option A may be different than the date at which you will be paid for Option B. For all problems Option B will pay either at the same time or strictly later than Option A.

4. For all decision questions, the date at which you will be paid is in the future. Once, the amount you will receive and the payment date are determined as explained above, you will be given an envelope to write your name, email address, the amount and the payment date. This information will be seen only by Professor Ozbay, Director of the Experimental Economics Laboratory at the UMD, and his assistants. Your identity will not be a part of the data analysis and any identifying information will be destroyed after the payment. You will be assigned a participant number, and only the participant number will remain in the data set.

5. When you come to the lab on the specified date anytime from 9:00am to 5:00pm, one of Professor Ozbay's assistants will be here to give your envelope with your specified amount. As a reminder to you, the day before you are scheduled to receive your payment, we will send you an e-mail notifying you the payment date. You may find Professor Ozbay's business card on your desk. If there is any problem regarding your payment, you should immediately contact Professor Ozbay.

Part II:

Once you have finished all ten sets of decision questions, you will be asked to fill a questionnaire.

If you have any questions, please raise your hand now, otherwise we will begin with the experiment.

B Survey Questions

1. Age:

2. Gender:

3. Academic major:

4. Do you work in paid employment?

5. Do you have a checking account?

6. At the end of last month (after you paid all your monthly bills and did all your monthly spending), about how much money remained in your checking accounts?

7. Do you have a separate savings account that differs from your checking account?

8. At the end of last month (after you paid all your monthly bills and did all your monthly spending), about how much money was in your savings accounts?

9. Do you have any credit cards?

10. At the end of last month (after you made your monthly payments to your credit card companies), what was the total remaining outstanding balances on all of your credit cards?

11. What is the average annual savings account interest rate in the United States?

12. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

    (a) More than $102

(b) Exactly \$102

(c) Less than \$102

(d) Do not know

(e) Refuse to answer

13. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

    (a) More than today

    (b) Exactly the same

    (c) Less than today

    (d) Do not know

    (e) Refuse to answer

14. A fair coin will be flipped 3 times. What is the probability that the coin will land on tails exactly once?

    (a) 1/8

    (b) 1/3

    (c) 3/8

    (d) 5/8

15. During the last twelve months, have you or anyone in your household ever bought lottery ticket for games like Lotto or Powerball, dailies like pick-4, or instant and scratch-off tickets?

    If answer to 15 is yes:

16. During the past twelve months, think about how often you or someone in your household bought such lottery tickets? Choose one of the following:

    (a) About every day

    (b) One to three times a week

    (c) Once or twice a month

    (d) A few times all year

    (e) Only once in the past year

    If answer to 15 is yes:

17. What is your favorite lottery game? Choose one of the following:

    (a) Large Multi-state lotteries like Mega Millions or Powerball

    (b) Other big jackpot lotteries like Michigan Lotto

    (c) Daily Games like Pick-3 or Pick-4

    (d) Instant/Scratch-off Tickets

    (e) No Favorite.

18. During the last twelve months, have you or anyone in your household ever gambled at a casino or in any other non-lottery outlet?

    If answer to 18 is yes:

19. During the past twelve months, think about how often you or someone in your household bought such lottery tickets? Choose one of the following:

    (a) About every day

    (b) One to three times a week

    (c) Once or twice a month

    (d) A few times all year

    (e) Only once in the past year

C Supplemental Results

C.1 Heterogeneity in PLS

Table C.1: Regression estimates of heterogeneous responses to PLS

	Delay payment		Switch point	
	(1)	(2)	(3)	(4)
PLS · Lottery player	0.103**	0.105**	–1.073**	–1.089**
	(0.043)	(0.041)	(0.445)	(0.415)
PLS · Female	–0.069*	–0.078*	0.801*	0.866**
	(0.041)	(0.041)	(0.415)	(0.419)
PLS · Savings > \$1000		–0.075**		0.724*
		(0.036)		(0.369)
Lottery player	–0.103	–0.109*	1.140*	1.184**
	(0.062)	(0.058)	(0.632)	(0.594)
Female	0.012	0.034	–0.330	–0.499
	(0.066)	(0.063)	(0.689)	(0.637)
Savings > \$1000		0.197***		–1.888***
		(0.056)		(0.587)
PLS	0.072***	0.111***	–0.704***	–1.083***
	(0.025)	(0.035)	(0.252)	(0.353)
Constant	0.752***	0.650***	3.451***	4.437***
	(0.051)	(0.062)	(0.511)	(0.631)
R^2	0.018	0.049	0.031	0.080
N	6720	6720	644	644

Note: Each column presents the results from a regression in which the dependent variable is either an indicator for choosing option B ("Delay payment") or the switch point. In the delay payment regressions, each observation is a subject making a choice in a question in a problem; in the switch point regressions, each observation is a subject's switch point for a problem. The regressions in columns (2) and (4) include the following regressors: an indicator for being a PLS problem, an indicator for being a self-reported lottery player, an indicator for having greater than \$1000 in combined savings and checking account balances, and interactions between the PLS indicator and each of the three heterogeneity variables (lottery, female, savings). Standard errors are robust to heteroskedasticity and account for subject-level correlation in random errors. Asterisks indicate standard levels of statistical significance. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

In Table C.2, we report difference-in-difference results based on other observable characteristics obtained from our survey data. The eleven variables that we consider are (i) whether or not the subject was an Economics or Finance major; (ii) whether or not the subject was engaged in paid employment; (iii) whether or not the subject had a savings account; (iv) whether or not the subject had a credit card; (v) whether the subject had a positive credit card balance or not; (vi) whether the savings + checking account balance net of any credit card balance was greater or less than \$1,000; (vii) whether or not the subject engaged in casino or other non-lottery gambling; (viii) whether the subject was older or younger than 21 years; (ix) whether the subject correctly answered a probability question or not; (x) hether or not the subject correctly answered a question on future purchasing power of savings and (xi) whether the subject thought that the current interest rate on savings was greater or less than 1%. As can be seen, in only one instance—positive v. zero credit card balance—do we detect that the introduction of PLS affects savings differently for one group over the the other comparison group. We find that the (small) group of subjects with a positive credit card do not respond at all to the introduction of PLS, while the (much larger) group of subjects with no credit card balance strongly increase savings with the introduction of PLS. This finding explains why we find a weak effect that people with low (gross of credit card balance) account balances respond more to PLS while net of the credit card balance, there is no effect.

One might be interested in whether the distribution of changes in switch points are affected by the introduction of PLS for different subgroups. In order to address this, we calculated the difference in switch points between problems (a)–(b), (a)–(c), (d)–(e), (d)–(f) and (d)–(g) and then summed these numbers up for each subject. We then conducted a series of *t*-tests (mean), Mann-Whitney tests (median) and Epps-Singleton (distribution) for each of the characteristics in Tables 5 and C.2. The former two tests largely replicate the same results as we have just reported. Specifically, a significant effect for gender and lottery status and a just insignificant effect on savings ($p = .126$); they do not, however, detect a difference depending on whether or not a positive credit card balance is carried. The Epps-Singleton test, in contrast, gives the same significance patterns for those gender, lottery status and savings; however, it does detect a difference based on credit card balance (1% level) and also whether or not the subject is an economics or finance major (6% level).

C.2 Structural Estimation Results: Restricted Models

Here we expand upon Table 6 from the main body of the text to further demonstrate the importance of jointly estimating risk, time and probability weighting parameters. Specifically, in Table C.3 we repeat the unrestricted model results but also consider two restricted models: linear probability weighting ($\alpha = 1$) and linear probability weighting and risk neutrality ($\alpha = 1$ and $\rho = 0$). As can be seen, when we restrict $\alpha = 1$, subjects appear substantially less risk averse and more patient. Furthermore, behavior appears much more random, with our estimates of λ significantly lower. When we additionally impose $\rho = 0$ (i.e., risk neutrality), we continue to observed biased estimates of time preferences, and a further decent into randomness, with our estimates of λ closer yet to 0.

Table C.2: Heterogeneous responses to PLS v. standard interest (Other characteristics)

			PLS v. Standard interest	
	Subgroup:	Share of sample	Δ Delay payment	Δ Switch point
	Econ/Finance Major	0.313	0.091***	–0.831**
			(0.034)	(0.344)
(i)	Other Major	0.687	0.088***	–0.852***
			(0.024)	(0.247)
	Eco/Fin – Other		0.003	0.021
	(Δ – in – Δ)		(0.041)	(0.425)
	Paid Employment	0.458	0.115***	–1.119***
			(0.029)	(0.309)
(ii)	Unemployed	0.542	0.067***	–0.616**
			(0.025)	(0.259)
	Employed – Unemployed		0.048	–0.503
	(Δ – in – Δ)		(0.039)	(0.403)
	Have Savings Account	0.771	0.082***	–0.761***
			(0.022)	(0.231)
(iii)	Don't Have Savings Account	0.687	0.112***	–1.115***
			(0.040)	(0.404)
	Savings Account Yes – No		–0.030	0.354
	(Δ – in – Δ)		(0.046)	(0.466)
	Have Credit Card	0.479	0.093***	–0.938***
			(0.025)	(0.258)
(iv)	Don't Have Credit Card	0.521	0.084***	–0.757**
			(0.029)	(0.305)
	Credit Card Yes – No		0.009	–0.181
	(Δ – in – Δ)		(0.039)	(0.400)
	Credit Card Balance > 0	0.132	0.003	0.033
			(0.029)	(0.305)
(v)	Credit Card Balance $= 0$	0.868	0.095***	–0.902***
			(0.021)	(0.222)
	Credit Card Balance $> 0 - = 0$		–0.092**	0.934**
	(Δ – in – Δ)		(0.036)	(0.378)
	Net Balance $\geq$ \$1000	0.500	0.069**	–0.659**
			(0.029)	(0.301)
(vi)	Net Balance $<$ \$1000	0.500	0.108***	–1.040***
			(0.025)	(0.261)
	Net Balance High/Low		–0.039	–0.381
	(Δ – in – Δ)		(0.039)	(0.399)
	N		6720	644

Note: This table mimics Table 5 in the main text, but uses other observable characteristics. Standard errors reported in parentheses are robust to heteroskedasticity and account for subject-level correlation in random errors. Asterisks indicate standard levels of statistical significance. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Table C.2: Heterogeneous responses to PLS v. standard interest (Other characteristics), Cont'd

			PLS v. Standard interest	
	Subgroup:	Share of sample	Δ Delay payment	Δ Switch point
	Casino Gambling (Yes)	0.385	0.091***	–0.893**
			(0.034)	(0.346)
(vi)	Casino Gambling (No)	0.615	0.082***	–0.814***
			(0.023)	(0.244)
	Casino Yes – No		0.003	–0.079
	(Δ – in – Δ)		(0.041)	(0.424)
	Age $\geq$ 21	0.573	0.092***	–0.921***
			(0.026)	(0.266)
(vii)	Age $<$ 21	0.427	0.084**	–0.738**
			(0.029)	(0.305)
	Age Old/Young		0.008	–0.183
	(Δ – in – Δ)		(0.038)	(0.405)
	Fair Coin (Correct)	0.292	0.094***	–0.884***
			(0.026)	(0.280)
(viii)	Fair Coin (Incorrect)	0.708	0.086***	–0.830*
			(0.025)	(0.257)
	Correct – Incorrect		0.008	–0.054
	(Δ – in – Δ)		(0.036)	(0.381)
	Savings/Inflation (Correct)	0.854	0.088***	–0.844***
			(0.021)	(0.217)
(ix)	Savings/Inflation (Incorrect)	0.146	0.093**	–0.854*
			(0.044)	(0.511)
	Correct – Incorrect		–0.005	0.010
	(Δ – in – Δ)		(0.049)	(0.555)
	Interest Rate $>$ 1%	0.563	0.102***	–0.978***
			(0.028)	(0.293)
(x)	Interest Rate $\leq$ 1%	0.437	0.078***	–0.743***
			(0.026)	(0.274)
	IR $>$ 1% – IR $\leq$ 1%		0.024	–0.234
	(Δ – in – Δ)		(0.039)	(0.402)
	N		6720	644

Note: This table mimics Table 5 in the main text, but uses other observable characteristics. Standard errors reported in parentheses are robust to heteroskedasticity and account for subject-level correlation in random errors. Asterisks indicate standard levels of statistical significance. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Table C.3: Estimation Results: Unrestricted and Restricted Models

	One Rationality Parameter			Separate Rationality Parameters		
Parameter	Full Model	Restricted Models $\alpha = 1$	Restricted Models $\rho = 0$; $\alpha = 1$	Full Model	Restricted Models $\alpha = 1$	Restricted Models $\rho = 0$; $\alpha = 1$
ρ	0.514	0.155	*0*	0.497	0.164	*0*
	$[0.44, 0.58]$	$[0.09, 0.22]$		$[0.42, 0.57]$	$[0.08, 0.25]$	
r	0.834	0.03	0	0.856	0.579	0.798
	$[0.30, 1.30]$	$[0.00, 0.97]$	$[0.00, 0.64]$	$[0.34, 1.33]$	$[0.00, 1.33]$	$[0.00, 1.85]$
α	0.752	*1*	*1*	0.768	*1*	*1*
	$[0.70, 0.81]$			$[0.72, 0.83]$		
λ	1.641	0.426	0.227			
	$[1.25, 2.14]$	$[0.34, 0.57]$	$[0.20, 0.27]$			
$\lambda_{\texttt{time}}$				1.47	0.442	0.283
				$[1.10, 2.02]$	$[0.31, 0.67]$	$[0.22, 0.39]$
$\lambda_{\texttt{PLS}}$				1.651	0.617	0.342
				$[1.22, 2.20]$	$[0.43, 0.87]$	$[0.29, 0.41]$
$\lambda_{\texttt{risk}}$				1.482	0.381	0.169
				$[1.10, 2.00]$	$[0.26, 0.57]$	$[0.15, 0.20]$
obs	9600	9600	9600	9600	9600	9600
LL	-4717.78	-4845.71	-4954.29	-4715.09	-4802.66	-4880.63

* Confidence intervals were obtained via a bootstrap procedure. In each of 400 iterations, we drew a random sample of subjects, with replacement, and then estimated the model's parameters. We then take the 2.5 and 97.5 percentiles from the distribution of estimates as our confidence interval. Note that we draw our random sample at the level of the subject, taking each selected subject's 100 observations. In the two right-hand columns, we report the results of estimations which restrict $\alpha = 1$ or the joint restriction $\alpha = 1$ and $\rho = 0$. Cells in italics indicate that the parameter was restricted to the particular value.

D Omitted Proofs

Proposition 1. *For any $\alpha < 1$ there exists a $p^* \in (0,1)$ such that for all $p < p^*$, $U^{pls} > U^{int}$.*

Proof. To prove this, it is enough to show that as p goes to 0, $U^{\texttt{PLS}}/U^{\texttt{INT}}$ goes to infinity. This is equivalent to show that $\lim_{p\to 0} w(p)(1+i/p)^{1-\rho} = \infty$.

$$\begin{aligned}
\lim_{p\to 0} w(p)(1+i/p)^{1-\rho} &= \lim_{p\to 0} \frac{(1+i/p)^{1-\rho}}{e^{(-\ln p)^{\alpha}}} \\
&= \lim_{p\to 0} \left(\frac{1+i/p}{e^{\frac{(-\ln p)^{\alpha}}{1-\rho}}}\right)^{1-\rho} \\
&= \lim_{z\to\infty} \left[e^{-\frac{z^{\alpha}}{1-\rho}} + ie^{z-\frac{z^{\alpha}}{1-\rho}}\right]^{1-\rho} \\
&= \infty
\end{aligned}$$

The first and second equalities rearrange the expression; the third equality comes from the change of variables $z = -\ln p$. The final equality comes from the fact that for $\alpha, \rho \in (0,1)$, $z - \frac{z^{\alpha}}{1-\rho} \to \infty$. □

Proposition 2. *For all $\alpha \in (0,1)$ and all $\rho \in (0,1)$, there exists $\hat{p} < 1$ such that for $p < \hat{p}$, the decision maker allocates all future consumption to the PLS device and that the amount of money devoted to future consumption, $x_{f,p}^{PLS}$ is larger than the amount devoted, $x_{f,i}^{INT}$ when only interest-only savings are available.*

Proof. We begin by showing that for p small enough, the consumer places all savings in the PLS device. To show this, it is enough to show that $1 - A(1 + i/p) > 0$ and $(A-1)(1+i) < 0$ for p sufficiently small. The proof will be complete if we can show that $\lim_{p\to 0} A = 0$ and $\lim_{pto0} A/p = 0$. Indeed, consider the first limit:

$$\begin{aligned}
\lim_{p\to 0} A &= \lim_{p\to 0}\left(\frac{(1-w(p))}{w(p)(1/p-1)}\right)^{1/\rho} \\
&= \lim_{z\to\infty}\left(\frac{1-e^{-z^\alpha}}{e^{-z^\alpha}(e^z-1)}\right)^{1/\rho} \\
&= \lim_{z\to\infty}\left(\frac{1}{e^{z-z^\alpha}-e^{-z^\alpha}}-\frac{1}{e^z-1}\right)^{1/\rho} \\
&= 0,
\end{aligned}$$

where the second equality comes from the change of variables $p = e^{-z}$ and the final equality comes from the fact that $\alpha \in (0,1)$ so that $z - z^\alpha \to \infty$ as $z \to \infty$.

Consider now the second limit:

$$\begin{aligned}
\lim_{p\to 0}\frac{A}{p} &= \lim_{p\to 0}\frac{1}{p}\left(\frac{(1-w(p))}{w(p)(1/p-1)}\right)^{1/\rho} \\
&= \lim_{z\to\infty} e^z\left(\frac{1-e^{-z^\alpha}}{e^{-z^\alpha}(e^z-1)}\right)^{1/\rho} \\
&= \lim_{z\to\infty}\left(\frac{e^{\rho z}-e^{\rho z-z^\alpha}}{e^{-z^\alpha}(e^z-1)}\right)^{1/\rho} \\
&= \lim_{z\to\infty}\left(\frac{1}{e^{(1-\rho)z-z^\alpha}-e^{-(\rho z+z^\alpha)}}-\frac{1}{e^{(1-\rho)z}-e^{-\rho z}}\right)^{1/\rho} \\
&= 0,
\end{aligned}$$

where again the second equality comes from the change of variables $p = e^{-z}$ and the final equality comes from the fact that $\rho, \alpha \in (0,1)$, so that $(1-\rho)z - z^\alpha \to \infty$ and $(1-\rho)z \to \infty$ as $z \to \infty$.

To prove the second part of the proposition — that the consumer will save more for future consumption with PLS than an interest-only device, we must show that:

$$\frac{\pi}{[e^{-rt}(w(p)(1+i/p)^{1-\rho}+1-w(p))]^{-1/\rho}+1} > \frac{\pi}{[e^{-rt}(1+i)^{1-\rho}]^{-1/\rho}+1}.$$

We can rewrite the above expression as:

$$\left[e^{-rt}(1+i)^{1-\rho}\right]^{-1/\rho} > \left[e^{-rt}(w(p)(1+i/p)^{1-\rho}+1-w(p))\right]^{-1/\rho},$$

which can further be rewritten as:

$$(1+i)^{1-\rho} < w(p)(1+i/p)^{1-\rho}+1-w(p).$$

By Proposition 1, we know that this inequality will be satisfied for p small enough. $\square$

E Preference for Skewness and the Attractiveness of PLS

In this section, we show that the analogs of Propositions 1 and 2 do not hold if decision makers have a preference for skewness à la Mitton and Vorkink (2007). To this end, suppose that a decision maker has \$1 to invest either in an interest-only account, which will generate a payment of $1+i$ at time $t>0$ or in a PLS account, which will generate a payment of $1+\frac{i}{p}$ with probability p and a payment of 1 with probability $1-p$. Trivially, the undiscounted utility to the the interest-only account is $1+i$. On the other hand, with a little algebra (to compute the variance and skewness of the lottery), one can show that the undiscounted utility of the PLS account is:

$$U^{\texttt{pls}} = 1+i-\frac{\tau}{2}i^2\left(\frac{1-p}{p}\right)+\frac{\phi}{3}\frac{1-2p}{\sqrt{p(1-p)}}.$$

Therefore, the preference for PLS vs. interest-only is determined by the sign of:

$$-\frac{\tau}{2}i^2\left(\frac{1-p}{p}\right)+\frac{\phi}{3}\frac{1-2p}{\sqrt{p(1-p)}}.$$

It is not difficult to see that, since $\tau>0$, the limit of this expression as $p\to 0$ is $-\infty$. This follows because $\frac{1}{p}\to\infty$ faster than does $\frac{1}{\sqrt{p(1-p)}}$. Thus, as $p\to 0$, the variance of the lottery increases faster than the skewness, which leads the decision maker to prefer the interest-only option. This is in contrast to the behavior of a decision maker who suffers from non-linear probability weighting of the form presented in Proposition 1.

Move now to the analog of Proposition 2. Letting $\delta=e^{-rt}$ for simplicity, the utility of a decision maker who invests x_c in current consumption, $x_{f,i}$ in an interest-only account paying interest i at time t and $x_{f,p}$ in a PLS account paying i/p with probability p at time t, is given by:

$$U(x_c,x_{f,i},x_{f,p}) = x_c+\delta\left((1+i)(x_{f,i}+x_{f,p})-\frac{\tau}{2}i^2x_{f,p}^2\left(\frac{1-p}{p}\right)+1[x_{f,p}>0]\cdot\left(\frac{\phi}{3}\frac{1-2p}{\sqrt{p(1-p)}}\right)\right).$$

It is of interest to note that the contribution of skewness to the utility function does not depend on the amount invested in the PLS asset, so long as it is positive. This creates technical issues because the utility function is no longer continuous.

If we make the substitution $x_c = \pi - x_{f,i} - x_{f,p}$, then the marginal contribution of money to PLS is:

$$-1 + \delta\left(1 + i - \tau i^2 x_{f,p}\left(\frac{1-p}{p}\right)\right)$$

and observe that, for a fixed $x_{f,p}$, this goes to $-\infty$ as $p \to 0$. Therefore, but for the discontinuity in the utility function at $x_{f,p} = 0$, the decision maker would never allocate money to a PLS device. However, consider the discrete change in utility going from $x_{f,p} = 0 \to x_{f,p} = p$. This is given by:

$$\Delta U = -p + \delta\left((1+i)p - \tau i^2 p(1-p) + \frac{\phi}{3}\frac{1-2p}{\sqrt{p(1-p)}}\right).$$

Observe that $\Delta U \to \infty$ as $p \to 0$. Therefore, in the limit, the decision maker will allocate an infinitesimally small amount to the PLS device. Then, depending on whether $\delta(1+i) \lesseqgtr 1$, the decision maker will allocate the rest either to current consumption of future consumption in an interest bearing account.