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# Energy-Using Durables: The Role of Time Discounting in Investment Decisions

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## Executive Summary

Markets for energy-using durables seem to be characterized by an "energy efficiency gap", the phenomenon that consumers could save on total costs if they bought high-efficiency products but often decide not to do so. This fact has been attributed to consumers undervaluing future cost savings relative to the upfront purchase price, possibly due to their high discount rates.

Factors influencing discounting behavior include the following:

1. Individuals' rates of pure time preference, i.e. the rate at which future utility is exchangeable for present utility

2. Uncertainty concerning product life, service reliability and future energy costs

3. Individuals' limited access to capital markets resulting in liquidity constraints

4. Difficulties obtaining and processing information regarding future running costs

The objective of the current research was to develop a descriptive model of discounting behavior which disentangles the effects of pure time preferences from other potentially decisive factors in the context of financial decision making and to test the model with novel experimental data. The data was collected from a representative sample of the German speaking Swiss population. We elicited discount rates, measures of risk aversion and other individual data relevant for decisions on energy-using durables. There were two different treatment groups: One group of the participants responded to hypothetical questions and received a flat participation fee, the other group was paid depending on their decisions in an incentive compatible manner.

The following results emerged:

1. We found a substantial incentive effect: People who responded to hypothetical questions exhibited an average discount rate of 47.5% p.a., compared to 36.4% p.a. of the incentivized group. Model estimates show that there is no significant difference between groups' preference parameters other than their levels of pure time preference. The incentive effect can be traced back to the behaviors of comparatively small subgroups of people in the hypothetical treatment who reacted strongly to two factors: skepticism about the certainty of future payments and liquidity constraints, both of which drove up discount rates considerably.

   We did not find any evidence whatsoever that participants in the hypothetical treatment did not do their best to respond conscientiously and honestly. We conjecture that the incentive effect is due to people's inherent difficulty of foreseeing how they will behave when they actually face real consequences of their choices. For this reason we recommend that the design of policy measures should be principally based on the analysis of real decisions.

2. Liquidity constraints are an important factor affecting people's behavior in the incentivized treatment group. We estimate that discount rates are 40% higher for liquidity-constrained individuals than for unconstrained ones who exhibit an average rate of time preference of more than 30% p.a. The magnitudes of these rates suggest that there are considerable obstacles to investment in energy-efficient durables even for people with unlimited access to capital markets.

3. Participants reported to be concerned about uncertain future energy costs and to have difficulties with assessing monthly energy costs. Both factors may play a crucial role in people's undervaluation of future energy cost savings. Product- and consumer-specific information on present values of expected running costs may help consumers in their decision making.

4. If our estimates of time preference rates are indeed manifestations of people's innate preferences, information and education will most likely not alter people's behavior. In this case, policy could influence relative prices of high-efficiency and low-efficiency durables directly via feebates, a combination of fees and rebates. This idea can be transferred to other aspects of the purchase decision, such as service, warranty and leasing contracts. In order to be able to quantify the relative magnitudes of fees and rebates, the extent of undervaluation of future costs will have to be assessed on a market-by-market basis.

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# 1 Introduction: The Efficiency Gap and the Role of Discounting

Markets for energy-using durables seem to be characterized by an anomaly which has become known as the "efficiency gap" (Howarth and Sanstad, 1995): the level of energy efficiency achieved is lower than the cost-effective level, judged by standard financial criteria. Market participants often do not invest in high-efficiency durables even though the present value of future energy cost savings more than offsets the higher purchase price of these products. Cost effectiveness is assessed by applying some reasonable market interest rate when calculating the present value of cost savings. Obviously, if people use comparatively higher discount rates in their private investment calculations they are less willing to pay a high purchase price upfront.

There is abundant empirical evidence documenting that discounting behavior exhibits a number of robust regularities (Frederick, Loewenstein, and O'Donoghue, 2002):

- Observed discount rates tend to be very high, often exceeding market interest rates by substantial margins, and vary considerably across individuals and across studies.
- Discount rates are not constant but rather decline with the time horizon, i.e. near-present events tend to get discounted much more heavily than events in the remote future. This type of behavior has been labeled "hyperbolic discounting" because the discount function does not exhibit an exponential curve degression, associated with constant discount rates, but rather a hyperbolic one, reflecting declining discount rates. Hyperbolic discounting entails extremely high discount rates in the short run. Therefore, observed average discount rates are likely to be very high, too, and depend on the time horizon over which they are measured.
- Discount rates exhibit a magnitude effect, i.e. discount rates for small amounts tend to be much higher than rates for large amounts.

There is also direct evidence of an efficiency gap. A considerable number of studies, the majority of which were conducted in the 1970's and 1980's in the U.S., estimated implicit discount rates inferred from purchase decisions. Table 1 summarizes these estimates of implicit discount rates by category of energy-using product.[1] Several observations emerge (DEFRA (2010), p.15):

- There is a wide range of discount rates, from 2% to 300%, both within and across categories.
- Most of the discount rates are considerably higher than market interest rates.
- Discount rates are lower when saving energy is the primary purpose of the investment.

Table 1: Estimated Implicit Discount Rates p.a.

| Category | Discount Rate |
|---|---:|
| Thermal insulation | 10 - 32% |
| Space heating | 2 - 36% |
| Air conditioning | 3.2 - 29% |
| Refrigerators | 39 - 300% |
| Lighting | 7 - 17% |
| Automobiles | 2 - 45% |

Sources: Train (1985), DEFRA (2010).

The variability of implicit discount rates for energy-using durables, reported in Table 1, can be interpreted in the light of the empirical facts on discounting behavior discussed above:

- Due to their comparatively low energy intensity, cost savings for refrigerators are relatively small and, because of the magnitude effect discussed above, are likely to get discounted more strongly than cost savings for, say, heating systems.
- Expected lifetimes may differ substantially between different product categories, which may affect estimates of implicit discount rates, particularly if consumers' discount rates are not constant over the time horizon.
- Finally, depending on the specific product, customers may belong to different socioeconomic groups, characterized by different levels of discounting. For instance, there is evi-

[1]For a review of methods used to estimate implicit discount rates see Train (1985). In all studies, assumptions have to be made concerning the lifetime of the product and the development of future energy costs. Consider the following simple stylized example: Suppose a consumer is indifferent between two products, a high-efficiency product H with a purchase price $p_H$ and running costs $c_H$, all accruing in $t = 1$, and a low-efficiency product L with price $p_L$ and running costs $c_L$ with $p_H > p_L$ and $c_H < c_L$. Assuming linear utility and equating the present value of total costs $p_H + c_H \exp(-\vartheta) = p_L + c_L \exp(-\vartheta)$, yields an implicit discount rate of $\vartheta = -\ln \frac{p_H - p_L}{c_L - c_H}$.

dence that low-income households exhibit comparatively high discount rates (Lawrance, 1991).

The prevalence of high and, compared to market interest rates, excessive discount rates suggest that people are likely to focus on the purchase price of the energy-using durable and pay less regard to future energy costs. What are the causes underlying high observed discount rates? Discounting behavior is influenced by conceptionally quite distinct determinants:

1. **Pure time preference.** One possible explanation is that measured discount rates reflect people's pure time preferences, i.e. the preferences people have for trading off early versus late consumption. In that case, people's choices are privately optimal and any attempts at changing behavior are bound to fail unless direct incentives are provided that change people's cost-effectiveness calculations in favor of energy-efficient products.

2. **Uncertainty.** Neither product lifetimes nor energy costs can be predicted with certainty. Therefore, discount rates are likely to contain a risk premium. This fact *per se* does not pose a problem for energy efficiency because it is rational to use a risk-adjusted discount rate when calculating present values of future running costs.[2]

3. **Liquidity constraints.** Typically, consumers do not face a universal constant rate at which they can borrow financial funds. Banks charge differential rates depending on applicants' credit default risk. Therefore, investments in energy-efficient durables may not pay off for consumers with high borrowing costs.

4. **Information.** People may ignore or be unable to use information optimally. If people either do not know what the future costs are or have difficulties translating them into meaningful numbers, their cost-effectiveness calculations may be systematically biased towards low-efficiency durables.

If people's discount rates reflect their true underlying time preferences there is *prima facie* no reason for policy intervention. However, the operation of energy-using durables is often associated with negative external effects, for instance $CO_2$ emissions from burning

[2]However, recent theoretical contributions have shown (Halevy, 2008; Epper, Fehr-Duda, and Bruhin, 2010) that uncertainty inherent in the future may not only generate high discount rates but also hyperbolic discounting, thereby leading to excessive short-term discount rates and procrastination.

fossil fuels, which may justify intervention. On the other hand, individuals' problems of acquiring and processing information constitute a case of bounded rationality leading to suboptimal choices, which not only causes private welfare losses but also exacerbates the extent of negative externalities.

The objective of this study is to develop and test a model of discounting behavior which disentangles the effects of pure time preferences from other decisive determinants and to identify starting points for policy recommendations.

# 2 Experimental Design

The majority of studies on discounting behavior is based on university students' responses to hypothetical questions (Frederick, Loewenstein, and O'Donoghue, 2002). There are several potential problems regarding reliability and generalizability of these data. First, discount rates inferred from hypothetical decisions may not reflect people's true preferences. This phenomenon has become known as "hypothetical bias". Whereas there is a large body of evidence on the effects of financial incentives on judgment and decision making suggesting that incentives generally make a difference (Camerer and Hogarth, 1999), studies investigating incentive effects on discounting are scarce and inconclusive. Therefore, we cannot be sure that true discount rates can be reliably inferred from hypothetical choices. Second, young highly educated people's time preferences as well as cognitive abilities may not be representative of the population. Moreover, they may face different constraints affecting their intertemporal choices. For these reasons, we subscribed to the following design principles for this study:

1. **Subject pool**: We collected data on discounting behavior of a representative sample of the German speaking Swiss population. Recruitment was conducted by "LINK Institut für Markt- und Sozialforschung".

2. **Panel structure**: It is a well-known fact that a considerable percentage of participants choose differently when confronted with identical decision situations at two different points in time (Hey and Orme, 1994; Sayman, Onculer, and Yolu, 2007). In order to be able to examine stability of aggregate behavior, we conducted two waves of otherwise identical experiments.

3. **Financial incentives**: Due to the possibility of hypothetical bias, economic experiments with monetary incentives are to be preferred to surveys with hypothetical questions. However, experiments on discounting behavior tend to be quite expensive: Financial incentives should be salient, i.e. the difference between delayed and present amounts, the interest payment, has to be comparatively large to induce participants to seriously consider their options. This requirement entails large amounts on the basis of which interest payments are calculated. Since both the principal amounts and the interest payments have to be paid out to participants, incentive costs are considerable. Hence, given the large number of participants necessary for representativity, monetary costs for incentivized experiments are substantial.

   In opposition to these requirements, experimental budgets are limited. Therefore, we decided to run two different treatments - a treatment condition *flat* where we only paid a participation fee, which amounted to CHF 20 for the first wave and CHF 50 for the second one, and a treatment condition *incent* where every single participant not only received the participation fee but also got paid in an incentive compatible manner. Real incentives were calibrated such that, on average, participants earned an additional amount of CHF 100 per wave. This approach enabled us to investigate the effects of financial incentives on revealed discount rates.

4. **Framing of decisions**: Even though our main focus lies on the underweighting of future energy costs we decided to frame the experimental decisions in abstract monetary terms rather than in energy-specific terms. The reason for our approach is the variability of observed discount rates depending on the nature of the product under consideration (see Table 1), suggesting that there are many different potential confounds involved which would have to be identified and controlled for in the experiment. Therefore, we favored a neutral design where subjects were fully informed about their options' consequences.

5. **Elicitation of risk preferences**: Since ignoring utility curvature results in biased estimates of discount rates we elicited participants' risk preferences, which are needed to control for diminishing marginal utility of money. Participants in the *incent* condition were paid in an incentive compatible manner also for the risk taking task.

6. **Questionnaire**: Aside from risk taking and time discounting tasks, participants were presented with an additional questionnaire after completion of the experimental sections of the survey. The main focus of this questionnaire was to elicit data on factors that are relevant for people's discounting behavior but cannot be directly measured by people's responses in the experiment. In particular, we asked a number of questions concerning purchase decisions for energy-using durables.

The main objective of this research project is developing and testing a descriptive model of discounting behavior which enables us to tease apart pure time preferences from other factors that influence discounting behavior. As potential candidates we have identified uncertainty, liquidity constraints and information deficits. While we are able to study the effects of uncertainty and liquidity constraints on people's discounting behavior, our experimental design is not suited to investigate problems of collecting and judging information, because participants were fully informed about their options' consequences. Therefore, assessment of information problems that are relevant for purchase decisions regarding energy-using durables was delegated to the complementary questionnaire.

## 3 Theoretical Framework: The Hyperbolic Preference Model

A descriptively valid model needs to be able to capture the dominant patterns of observed behavior. In the domain of intertemporal choice the dominant pattern is hyperbolic discounting, i.e. discounting at a non-constant rate declining over time. Therefore, we estimated a base model, the *hyperbolic preference model*, which allows for declining discount rates and which can be extended to accommodate effects of uncertainty and liquidity constraints. In the following, we briefly outline how we model discounting behavior.[3] Consider a choice between a smaller sooner payoff $x_1$ at time $t_1$ and a larger later payoff $x_2$ at $t_2$. At the present, these payoffs are equally valuable to the decision maker if the discounted utility of $x_1$ equals the discounted utility of $x_2$, i.e. if

$$d(t_1)u(x_1) = d(t_2)u(x_2) \tag{1}$$

[3] Details of the econometric specification are discussed in Appendix H.

holds, where $u(.)$ denotes the utility of monetary payoffs and $d(.)$ denotes the respective discount function. According to standard economic theory the discount function declines exponentially in time $t$, i.e. $d(t) = e^{-\eta t}$ with $\eta$ reflecting the constant rate of time preference. The empirical evidence, however, casts doubt on the assumption of constant discounting. Therefore, the discount function has to be modeled flexibly such that it can accommodate non-constant discounting. In our model, the discount function is specified as

$$d(t) = \begin{cases} e^{-\eta t^{1-\gamma}} & \text{if } \gamma < 1 \\ t^{-\eta} & \text{if } \gamma = 1 \\ e^{\eta t^{1-\gamma}} & \text{if } \gamma > 1 \end{cases}, \tag{2}$$

where $\eta > 0$ reflects the level of impatience, the constant component of time preference, and $\gamma$ captures how impatience evolves over time (Bleichrodt, Rohde, and Wakker, 2009). Hyperbolic discounting, i.e. decreasing impatience, is captured by $\gamma > 0$, constant impatience by $\gamma = 0$ .

As Equation 1 reveals, the intertemporal tradeoff between $x_1$ and $x_2$ also depends on the utility function $u$. Generally, $u$ exhibits diminishing marginal utility, i.e. $u$ is concave. If, as was done in most previous studies, linearity of utility is assumed when in fact it is concave, discount rates are overestimated. For this reason, we also elicited participants' risk preferences from which we could infer the curvature of the utility function, characterized by the parameter $\rho$. In order to isolate marginal utility from probabilistic risk attitudes we also estimated the parameters of a non-linear probability weighting function, $\alpha$ and $\beta$, which capture the often observed dependence of risk taking behavior on the level of probability $\overline{p}$.

Our model will be extended by assuming that preference parameters depend linearly on observed individual characteristics, such as feeling uncertain about future payments or being liquidity-constrained. When we examine the effects of these characteristics, represented by binary variables $U$ (for uncertainty) and $C$ (for constraint), respectively, we make the behavioral parameters $\theta$ linearly dependent on characteristic $X \in \{U, C\}$, such that $\theta = \theta_0 + \theta_X \times X$, where $\theta$ may be any one of the utility, discounting or risk parameters $\rho, \eta, \gamma, \alpha, \beta$. The coefficient of $X$, $\theta_X$, measures the effect of $X$ on the respective parameter over and above the base level $\theta_0$.

# 4 Analysis of Experimental Data

In this section, we use data from a broad sample of the Swiss-German population and examine how individuals discount future outcomes. First, the experimental procedures and data are presented. Second, we analyze aggregate discounting behavior at the descriptive level. Finally, we present parametric estimates of individuals' time preference parameters, accounting for uncertainty and liquidity constraints as additional explanatory factors.

## 4.1 Experimental Procedures and Data

The LINK Institute recruited a total of 554 prospective participants from their internet panel in May and June 2009. Both treatment groups, *flat* and *incent*, were recruited separately according to the same sampling scheme based on three types of socio-economic attributes: gender, age class and employment status. Sampling and actual participation quotas are shown in Table 15 in Appendix A. Actual quotas by and large agree with sampling quotas. Therefore, selection appears not to have been a problem. About 60% of the persons approached by LINK completed the first wave of the experiments, resulting in 192 participants in the *flat* group and 140 participants in the *incent* group. Participation in the second wave declined to 160 and 114 respondents, respectively.

Shortly after recruitment prospective participants received a letter containing the experimental instructions and instructions how to access the internet platform which enabled them to take part in the experiment. The platform was active during a period of about two weeks.[4] People who did not participate were invited again by email.[5]

After participants had logged into the platform, the survey began with either the time discounting or the risk taking experiment first. Participants were assigned randomly to the respective order of the experimental tasks. After completion of the experimental tasks they filled out the questionnaire. When they had finished their inputs they received a confirmation of participation by email and were paid in cash, sent by registered mail, within the following 48 hours. *Flat* participants received a participation fee of CHF 20, which was considered by

[4]In case of technical problems or other issues participants could call our help desk number anytime or contact us via email.

[5]Candidates for the *flat* group were approached a third time if they had not responded earlier. Since the first two *flat* time slots overlapped with school holidays we gave *flat* candidates another opportunity to take part in the study, resulting in a larger number of *flat* participants.

LINK to be an adequate compensation for a one-hour experiment. To encourage continued participation this fee was raised to CHF 50 in the second wave. *Incent* participants were paid the same participation fee plus, on average, CHF 100 per wave. The actual amounts were determined by one random draw from participants' responses in each of the two experimental tasks. The outcomes of the selected risky decisions were paid out immediately with the participation fees, whereas participants' delayed earnings were paid out at their due dates.

The experimental tasks, which generated the observations on the relevant variables used for estimating the behavioral model, can be described as follows.

1. **Time discounting task**: Participants had to choose between a fixed later outcome $x_2$ at $t_2$ and a smaller sooner outcome $x_1$ at $t_1$ for a total of 21 varying amounts $x_1$ (see Figure 3 in Appendix B for an example). This procedure yielded an estimate of the *smaller sooner amount* $x_1$ which made the participant indifferent to receiving $x_2$ at the later date. There were 28 decisions of this kind with varying amounts $x_2 \in [20, 80]$ and timings $\{t_1, t_2\} \in [2days, 8months]$. Amounts were chosen to reflect the order of magnitude of potential cost savings of future running costs.

2. **Risk taking task**: Participants were presented with 20 different decisions. Each one involved a specific lottery $(\overline{x}, \overline{p}; \underline{x})$, $\overline{x} > \underline{x}$, paying off CHF $\overline{x}$ with probability $\overline{p}$ and $\underline{x}$ otherwise, and a list of 21 certain amounts, ranging from $\overline{x}$ to $\underline{x}$ (see Figure 4 in Appendix B). Participants had to indicate whether they preferred the lottery or the certain amount for each one of these certain amounts on the list. This procedure provided us with an estimate of the lottery's *certainty equivalent* $y$, the certain amount which generates the same utility as the lottery. The lottery payoffs were commensurate to the respective delayed ones and ranged from CHF 0 to CHF 80, with varying probabilities.

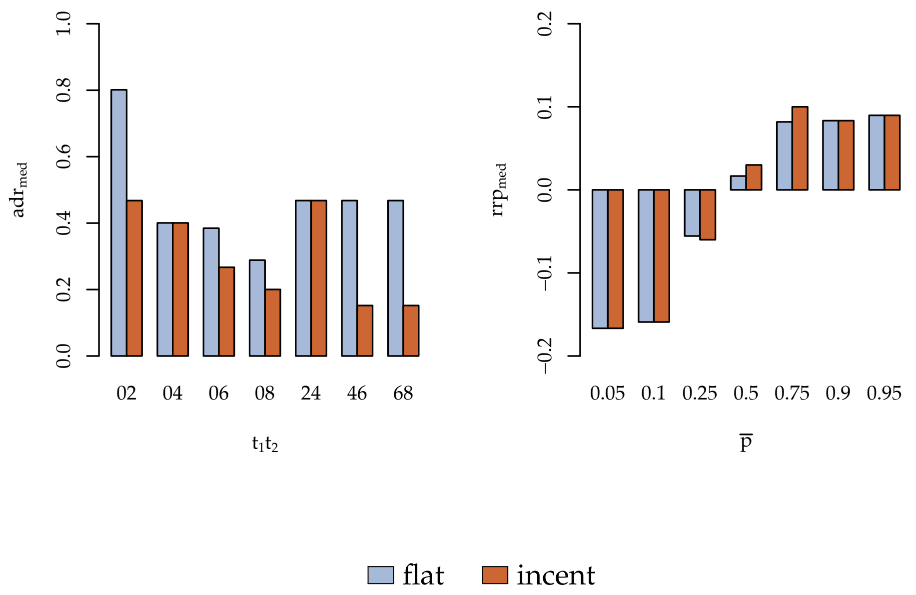
### 4.2 Results: Aggregate Discounting Behavior

We will first present findings for wave 1 of the experiments and then comment on the stability of behavior by comparing wave 1 with wave 2.

**Result 1 (Descriptive Results on Aggregate Behavior)** *On average, observed behavior features the typical patterns documented in the empirical literature: First, discount rates are considerably* *higher than market interest rates and decline in time horizon. Second, there is only moderate average risk aversion in the data, with relative risk premia increasing in the probability of the better outcome.*

*Support.* The median individual discount rate amounts to 46.78% p.a. (median absolute deviation (*mad*): 46.83).[6] The left panel in Figure 1 shows that observed median discount rates $adr_{med}$ for tradeoffs $t_1t_2$ between the sooner date $t_1 = 0$ (0 stands for two days) and later dates $t_2 \in \{2, 4, 6, 8\}$ months decline in time horizon $t_2$, thus rendering support for hyperbolic discounting in our data.[7]

Figure 1: Median Discount Rates by Tradeoff and Relative Risk Premia by Probability




The median individual relative risk premium $rrp_{med}$ is equal to 0.017 (*mad*: 0.055).[8] That is, we find only moderate degrees of average risk aversion in our data. The right panel in Figure

[6]The normalized measures for impatience and risk aversion are calculated by first aggregating over all the choices by the participant (median over all observations of a participant) and then aggregating over participants (by taking the median of the individual medians). The reported dispersion measures (*mad*) therefore give an indication about heterogeneity *among* participants in the data. "Normalized" annualized discount rates are defined by $adr = -(t_2 - t_1)^{-1} \ln(x_1/x_2)$ and aggregated, where $t_2 - t_1$ denotes the delay between the (given) later amount $x_2$ and the observed earlier amount $x_1$.

[7]A similar conclusion can be drawn when comparing tradeoffs $t_1t_2$ with a fixed delay $t_2 - t_1$, but different locations on the time axis, i.e. the tradeoffs 02, 24, 46 and 68 with a delay of two months each. We do not find any evidence of a magnitude effect at the level of aggregate behavior. Over the range of payoffs used in the experiment, there is no significant relationship between magnitude of payoffs and magnitude of discount rates.

[8]"Normalized" risk premia *rrp* are defined as $rrp = (\text{ev} - y)/\,\text{abs}(\text{ev})$, with $y$ denoting the lottery's certainty equivalent and ev its expected value.

1 indicates that risk attitudes depend on the probability of the better outcome $\overline{p}$, however. Risk seeking for small-probability gains, $rrp_{med} < 0$, and risk aversion for high-probability gains, $rrp_{med} > 0$, is consistent with nonlinear weighting of probabilities, incorporated in modern theories of decision making under risk, such as Rank Dependent Expected Utility Theory (Quiggin, 1982) or Cumulative Prospect Theory (Tversky and Kahneman, 1992).

*Discussion.* So far, our results contain no surprise. Qualitatively, we find the expected patterns for both time discounting and risk taking behavior. Despite being considerably larger than market interest rates, observed discount rates lie in the lower range of previously reported ones (Frederick, Loewenstein, and O'Donoghue (2002), Table 1). One possible reason for this difference may be differing subject pools. While our participants stem from a representative field sample, most other studies took place at universities or in developing countries and, hence, use either a highly selective sample of participants or subjects facing totally different economic environments. Figure 1 also reveals quantitative differences in time discounting between the *flat* and *incent* conditions. Our next result is concerned with this finding.

Table 2: Median Discount Rates by Tradeoff $t_1t_2$

| | $t_1t_2$ | flat (n=192) | incent (n=140) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.801 | 0.468 | 0.333 | 0.000 |
| 2 | 04 | 0.401 | 0.401 | 0.000 | 0.008 |
| 3 | 06 | 0.385 | 0.267 | 0.118 | 0.002 |
| 4 | 08 | 0.289 | 0.200 | 0.088 | 0.001 |
| 5 | 24 | 0.468 | 0.468 | 0.000 | 0.001 |
| 6 | 46 | 0.468 | 0.152 | 0.316 | 0.014 |
| 7 | 68 | 0.468 | 0.152 | 0.316 | 0.110 |

$n$ denotes number of participants.

$\Delta adr_{med}$ denotes the difference between condition-specific discount rates.

**Result 2 (Incentive Effects: Wave 1)** *There is clear evidence for a hypothetical bias in time discounting but not in risk taking, i.e. discounting behavior under real incentives is significantly different from behavior under hypothetical conditions. Participants facing hypothetical rewards in the time discounting task exhibit higher impatience compared with participants facing real monetary incentives. The effect is substantial and statistically significant. It is predominantly a level effect, but appears to be less pronounced when intertemporal tradeoffs involve more distant outcomes. It is improbable that selection caused the systematic condition-specific differences in discounting behavior.*

Table 3: Median Relative Risk Premia by Probability $\overline{p}$

| | $\overline{p}$ | flat (n=192) | incent (n=140) | $\Delta rrp_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 0.05 | -0.167 | -0.167 | 0.000 | 0.103 |
| 2 | 0.10 | -0.159 | -0.159 | 0.000 | 0.846 |
| 3 | 0.25 | -0.056 | -0.060 | 0.004 | 0.431 |
| 4 | 0.50 | 0.017 | 0.030 | -0.013 | 0.345 |
| 5 | 0.75 | 0.082 | 0.100 | -0.018 | 0.499 |
| 6 | 0.90 | 0.083 | 0.083 | 0.000 | 0.680 |
| 7 | 0.95 | 0.090 | 0.090 | 0.000 | 0.886 |

$\overline{p}$ denotes the probability of the better outcome.

$n$ denotes number of participants.

$\Delta rrp_{med}$ denotes the difference between condition-specific risk premia.

*Support.* We conducted two different tests on incentive effects. First, we assessed the differences between group-level medians. Second, we performed statistical tests to evaluate the differences of individual-level measures of impatience and risk attitudes between the two conditions.

Figure 1 gives a first indication about the effects of real monetary incentives on intertemporal and risky choices. For each intertemporal tradeoff, median annualized discount rates $adr_{med}$ in the *flat* condition are at least as large as in the *incent* condition (left panel).[9] There seems to be no treatment effect for risk-taking behavior (right panel). However, these figures only reveal differences in the medians of the distributions and, hence, are not informative of individual-level differences.

Our conclusions are confirmed when comparing individual median discount rates between the two groups. As it turns out, participants facing hypothetical questions show much higher impatience (47.51% p.a. (*mad*: 47.91)) than those facing real monetary incentives (36.41% p.a. (*mad*: 31.45)). The difference is substantial (11.10 percentage points) and of high statistical significance (Wilcoxon rank sum test renders a $p$-value of 0.015; alternative hypothesis: $arp^{flat} > arp^{incent}$). We also carried out the same test for observed risk taking, but did not find a significant incentive effect in this domain (0.017 (*mad*: 0.064) *(flat)* vs. 0.017 (*mad*: 0.047) *(incent)*, $p$-value of 0.636).

Because of the systematic patterns in Figure 1 it makes sense to conduct these tests for each temporal tradeoff $t_1t_2$ and probability $\overline{p}$ separately. The $p$-values in Tables 2 show that the

[9] Median differences are listed in the fifth column ($\Delta adr_{med}$) of Table 2.

distributions of individual discount rates appear not to be equal between the two conditions. Rather, individual median discount rates for participants in the *flat* condition are higher than the rates for participants in the *incent* condition.[10] This incentive effect is highly significant for almost every tradeoff. In contrast, there seems to be no such effect for risk taking behavior: For no level of probability do we find significant differences between individual risk premia in the two conditions.

*Discussion.* Our results pose a number of questions. First, and most importantly, is selection responsible for the significant differences between the two groups? Or did the lack of incentives lead participants to exert less effort? Is the incentive effect just an artifact of carelessness or sticking with the default option implemented in the choice menus? Here we address these important questions, and hope to convince the reader that the systematic incentive effect is driven neither by selection nor by lack of effort.

Concerning the issue of selection, there is no plausible reason why more impatient participants should have self-selected into the *flat* condition, rather than into the *incent* condition. Participants were informed about payment procedures at recruitment but were not aware of any other treatment we ran. Moreover, the participants in both conditions seem to represent the sampling quota pretty well, and the socioeconomic characteristics used for sampling do not show significant differences between conditions.[11] These findings suggest that other reasons than selection drive the systematic differences in time discounting behavior.

When we started this study, we did not expect a systematic behavioral effect, but conjectured that, if at all, the lack of incentives might induce people to put less effort in decision making because they did not have to assess and weight real consequences of their decisions. If this hypothesis were true, people confronted with hypothetical choices should be more likely to stick with the default option in the choice menus: To avoid that participants had to click on each line of the choice menu to indicate their preferred choice, we defined the later options and the risky options as respective defaults (see Figures 3 and 4 in Appendix B). Participants then had to change the choices they did not agree with. In the extreme case, a participant who just clicked through the choice menus would therefore reveal perfect patience in the time discounting task and pronounced risk seeking in the risk taking task. This is clearly not the

[10] All the tests we performed are two-sided Wilcoxon rank sum tests.
[11] Socioeconomic characteristics for each group are listed in Table 15 in the Appendix.

case here. Choices at the boundaries of the decision sheets are very rare, and their frequencies do not differ across the two conditions.[12]

Obviously, the lack of incentives need not lead to such extreme responses. Participants facing hypothetical choices may just be "lazier" than others. Given the construction of the choice menus, we would expect that presumably lazier participants in the *flat* condition exhibited more patience than did participants in the *incent* condition. However, the opposite is the case. Moreover, any explanation involving lack of effort would also apply to people's choices in the risk taking task where we do not find any notable difference between the two conditions.

Another argument against lack of effort concerns response times. Presumably, people who do not think thoroughly about their decisions take less time to indicate their choices. If this hypothesis were true, we should find that participants in the *flat* condition needed less time for their choices than participants in the *incent* condition. Once again, the opposite result emerges. Comparing average response times shows that participants in the *flat* condition used more time (13 seconds) than participants in the *incent* condition (12 seconds).[13] The difference between the two groups is insubstantial, albeit statistically significant ($p$-value approximately zero, based on a one-sided Wilcoxon rank sum test). Therefore, it is improbable that lack of effort drives the treatment effect.

Why the lack of monetary incentives induces such differences in responses is an open question. We can only speculate here. Presumably, in hypothetical decision situations, it may be difficult for the decision maker to put herself into the shoes of someone who actually faces real monetary consequences.[14]

In the following, we examine the temporal stability of behavior across the two waves of the experiment, which took place eight months apart from each other.

**Result 3 (Incentive Effects: Temporal Stability)** *When confronted with the same choice tasks eight months later, flat participants exhibit essentially the same behavior as in the first waves, whereas incent participants became significantly more patient over the course of time.*

[12]2.61% *(flat)* and 3.19% *(incent)* of all observations in the time discounting task contain a zero discount rate.

[13]Obviously, this measure is only a proxy for the time it really took participants to make their choices. Potential confounds are different latencies and breaks during the experiment. These confounding factors, however, should have affected participants in both conditions equally.

[14]This is not to say that she does not try to do so.

*Support.* Participation between wave 1 and wave 2 declined about equally in both conditions (20% (*flat*), 22.8% (*incent*)). Judged by the distribution of socioeconomic characteristics, displayed in Table 16 in Appendix A, the structure of the samples remained stable across waves.

For the 160 (of 192 in wave 1) participants in the *flat* group, there is no significant difference between observed discount rates in the two waves (47.14% in wave 1 vs. 48.24% in wave 2, $p$-value of 0.573 (two-sided)). For the *incent* participants responding in both waves (114 of 140 participants), median discount rates declined from 29.75% in wave 1 to 20.03% in wave 2 eight months later. The difference between discount rates in the two waves is statistically highly significant and positive (judged by a one-sided Wilcoxon signed-rank test comparing individuals' choices in the first and the second wave we get a $p$-value of approximately zero).[15]

Examining changes at the level of tradeoffs, we do not find a consistent pattern for the *flat* condition (see Table 4). Therefore, we cannot reject the hypothesis that the differences between wave 1 and wave 2 behaviors are due to random errors on the 5%-level, except for the tradeoff between 6 months and 8 months, $t_1 t_2 = 68$. Table 5 documents a systematic change in behavior for the *incent* condition and each tradeoff separately. It provides $p$-values for Wilcoxon rank-sum tests for the alternative hypothesis that individual median discount rates are larger in wave 1 than in wave 2 for each tradeoff.[16]

Table 4: Wave 1 vs. Wave 2: Median Discount Rates for *flat* Condition

| | $t_1 t_2$ | wave1 (n=160) | wave2 (n=160) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.801 | 0.801 | 0.000 | 0.396 |
| 2 | 04 | 0.401 | 0.401 | 0.000 | 0.621 |
| 3 | 06 | 0.385 | 0.385 | 0.000 | 0.227 |
| 4 | 08 | 0.289 | 0.289 | 0.000 | 0.130 |
| 5 | 24 | 0.468 | 0.468 | 0.000 | 0.085 |
| 6 | 46 | 0.468 | 0.468 | 0.000 | 0.873 |
| 7 | 68 | 0.468 | 0.468 | 0.000 | 0.995 |

$n$ denotes number of participants.

$\Delta adr_{med}$ denotes the difference between wave-specific discount rates.

[15] As Appendix C documents, we do not find systematic differences when comparing risk preferences between the two waves.

[16] The $p$-values for the alternative hypothesis that individual median discount rates are smaller in wave 1 than in wave 2 are simply one minus the $p$-values reported in the tables.

Table 5: Wave 1 vs. Wave 2: Median Discount Rates for *incent* Condition

| | $t_1t_2$ | wave1 (n=114) | wave2 (n=114) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.468 | 0.468 | 0.000 | 0.052 |
| 2 | 04 | 0.401 | 0.234 | -0.167 | 0.001 |
| 3 | 06 | 0.267 | 0.267 | 0.000 | 0.000 |
| 4 | 08 | 0.200 | 0.200 | 0.000 | 0.000 |
| 5 | 24 | 0.152 | 0.152 | 0.000 | 0.000 |
| 6 | 46 | 0.152 | 0.152 | 0.000 | 0.001 |
| 7 | 68 | 0.152 | 0.152 | 0.000 | 0.003 |

$n$ denotes number of participants.

$\Delta adr_{med}$ denotes the difference between wave-specific discount rates.

*Discussion.* While we cannot present a conclusive reason for the decline of *incent* participants' discount rates, we hypothesize that participants reacted to changes in their economic environment. We conducted the first wave of our experiment in June and August 2009, a period of economic crisis in which participants may have felt uncertain about their future prospects. When the second wave took place, the overall economic situation had already improved considerably. Obviously, in times where there is much uncertainty about future employment or labor income, or, maybe even worse, when the economic situation restricts households' scope of action, people may be better off opting for earlier rather than later payment. These changes in the economic environment seems to have had no effect on *flat* participants' hypothetical choices. In our view, this finding underscores the complexity of factors that impact behavior in real decision situations but seem to make little difference to hypothetical choices.

In the following we employ a descriptive model on the wave 1 data, the base *hyperbolic preference model*, which allows a compact representation of group-level behavior.[17] Table 7 lists all the parameters used in both the base model and its extensions.

[17]While responses in wave 2 are different from wave 1 for the *incent* group, qualitative insights remain unchanged. Therefore, we only present estimates for wave 1 for which we have a larger number of observations.

Table 6: Hyperbolic Preference Model

flat

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.112 | 0.036 | 3.092 | 0.002 |
| $\eta$ | 0.457 | 0.022 | 20.895 | 0.000 |
| $\gamma$ | 0.230 | 0.037 | 6.166 | 0.000 |
| $\alpha$ | 0.637 | 0.011 | 60.495 | 0.000 |
| $\beta$ | 0.158 | 0.016 | 10.044 | 0.000 |
| participants | | | | 192 |
| parameters | | | | 7 |
| observations | | | | 8873 |
| $log\mathcal{L}$ | | | | -31353 |

p.e.: parameter estimate, s.e.: standard error.

incent

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.152 | 0.039 | 3.916 | 0.000 |
| $\eta$ | 0.366 | 0.021 | 17.666 | 0.000 |
| $\gamma$ | 0.166 | 0.049 | 3.378 | 0.001 |
| $\alpha$ | 0.630 | 0.012 | 53.177 | 0.000 |
| $\beta$ | 0.167 | 0.017 | 9.699 | 0.000 |
| participants | | | | 140 |
| parameters | | | | 7 |
| observations | | | | 6446 |
| $log\mathcal{L}$ | | | | -22334 |

Table 7: Model Parameters

| | Effects | Description | Interpretation |
|---|---|---|---|
| Utility | | | |
| $\rho$ | $u(x)$ | index for concavity | $\rho > 0$: diminishing marginal utility |
| Discounting | | | |
| $\eta$ ($\eta_0$) | $d(t)$[1,2] | rate of time preference ($U, C = 0$) | for $\gamma = 0$: discount rate $\eta$ is constant |
| $\eta_U$ | $d(t)$[1,2] | effect of $U = 1$ on time preference | $U = 1$: uncertainty-sensitive participants |
| $\eta_C$ | $d(t)$[1,2] | effect of $C = 1$ on time preference | $C = 1$: liquidity-constrained participants |
| $\gamma$ ($\gamma_0$) | $d(t)$[1] | index for decreasing impatience ($U, C = 0$) | $\gamma = 0$ ($\gamma > 0$): exponential (hyperbolic) |
| $\gamma_U$ | $d(t)$[1] | effect of $U = 1$ on hyperbolicity | $U = 1$: uncertainty-sensitive participants |
| $\gamma_C$ | $d(t)$[1] | effect of $C = 1$ on hyperbolicity | $C = 1$: liquidity-constrained participants |
| $\lambda_0$ | $d(t)$[2] | baseline hazard probability | hazard probability for $U = 0$ group |
| $\lambda_U$ | $d(t)$[2] | effect of subjective uncertainty | additional hazard probability for $U = 1$ |
| Probability Weighting | | | |
| $\alpha$ | $w(p)$ | index for curvature | $\alpha > 0$: inverted S-shaped function |
| $\beta$ | $w(p)$ | index for elevation | $\beta > 0$: optimistic weighting |

[1] Component of *hyperbolic preference model*. [2] Component of *hazard rate model*. For further details see Appendix H and I.

**Result 4 (Hyperbolic Preference Model)** *Participants in both conditions exhibit hyperbolic discounting. Estimates for the two conditions differ only with respect to the magnitudes of the constant component of time preference, with participants facing hypothetical choices being significantly more impatient, thus corroborating our descriptive finding that the incentive effect is predominantly a level effect.*

*Support.* Table 6 shows estimated model parameters for the *hyperbolic preference model*. This model allows for non-constant discounting and controls for diminishing marginal utility using the experimental risk data.

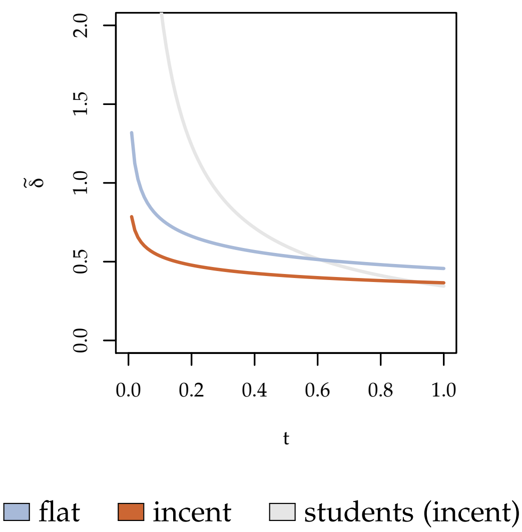
Comparing the *flat* and the *incent* groups' parameters renders the following results: First, both groups have very similar risk preferences (parameters $\rho$, $\alpha$ and $\beta$). The 95% confidence intervals of all the risk parameters overlap for the two groups.[18] Controlling for the concavity of utility, $\rho$, does not contribute much to explaining the large discount rates found at the descriptive level (see Result 1). Second, the estimated constant component of time preference, $\eta$, of the *flat* group, 45.7%, is significantly higher than that of the *incent* group, 36.6% (inferred from the 95% confidence intervals of the parameter estimates). Third, the two groups do not differ significantly with respect to the extent of hyperbolic discounting, visible in the similar parameter values of $\gamma$, which corroborates that the hypothetical bias manifests itself predominantly as a level effect.

Figure 2 depicts these results graphically. It shows time preference rates $\tilde{\delta}$ inferred from the parameter estimates of $\eta$ and $\gamma$ for the two groups, *flat* (blue) and *incent* (red), in our data.[19] The *flat* group's rate of time preference lies above the *incent* group's rate of time preference over the whole range of time delays. Consistent with disjunct confidence intervals of the estimates of $\eta$ (but overlapping ones for the estimates of $\gamma$), these rates show a similar decline in time horizon, corroborating that the incentive effect can be characterized as a level effect.

[18]The probability weighting function, represented by the parameters $\alpha$ and $\beta$, serves to isolate diminishing marginal utility from probabilistic risk aversion (see Wakker (1994)). It takes the typical inverted S-shaped form ($\alpha > 0$) for both groups. Comparing the curvature ($\alpha$) and the elevation ($\beta$) parameter estimates between the *flat* and the *incent* groups indicates no significant differences.

[19]$\tilde{\delta}$ is defined as $-t^{-1}\ln(\tilde{x}_1/x_2)$, where $\tilde{x}_1$ denotes the sooner amount predicted by the estimated model parameters, and $x_2$ denotes the (given) later amount (see also Appendix H). The graph also shows the curve for a reference group of university students who were confronted with real monetary incentives within the same payoff range (gray), which will be discussed below.

Figure 2: Inferred Time Preferences $\tilde{\delta}$




*Discussion.* The hypothetical bias in our data is predominantly a level effect. The group of participants who faced hypothetical choices reveal a significantly higher level of the constant component of time preference than the group of participants who faced real monetary incentives. However, we do not find any notable difference in the preference parameters for hyperbolic discounting, utility curvature, and probabilistic risk attitudes.

These findings pose the question of how the difference in impatience between the two groups can be explained. Since there is no reason why participants' average preferences should differ across treatment groups (they were randomly selected from the same population), a useful model of time discounting should be able to account for this difference by identifying an underlying cause, such that, when controlling for it, both groups can be represented by the same values of preference parameters. In other words, the incentive effect should be attributable to factors other than pure preferences. A promising candidate is uncertainty inherent in the future. The effects of liquidity constraints, the second focus of our analysis, will be discussed in Section 4.4.

## 4.3 Results: Inherent Uncertainty

If the future is perceived to be uncertain discount rates contain a risk premium over and above the pure rate of time preference. In the context of the decision situations in the experiment, inherent uncertainty pertains to the probability that participants will not receive their promised rewards. Therefore, we collected data on individuals' perceptions of this possibility in the questionnaire in order to gauge the potential effects of decision-specific uncertainty on discounting. The resulting indicator, therefore, is constructed from participants' self-reports. Clearly, when people have to decide on which energy-using durable to buy, different dimensions of future uncertainty, such as uncertain lifetime, service reliability and future energy costs, will play a role, but these dimensions are not *behaviorally* relevant in the experiment here. However, we will also present participants' reports of their perceived uncertainty regarding future energy costs below.

**Result 5 (Descriptive Results on Inherent Uncertainty)** *A minority of participants stated that they perceived the payoffs from the experiment as uncertain. The percentage of uncertainty-sensitive types (sensitive types for short) is considerably higher in the flat condition (27 out of 192 participants) than in the incent condition where only 7 out of 140 participants expressed this view. Within the flat group, sensitive types exhibit much higher discount rates than insensitive types do. We conclude that inherent uncertainty may provide at least a partial account for the incentive effect in our data.*

Table 8: Effects of Uncertainty: Median Discount Rates for *flat* Condition

| | $t_1t_2$ | $U = 0$ (n=165) | $U = 1$ (n=27) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.801 | 1.529 | 0.728 | 0.000 |
| 2 | 04 | 0.401 | 0.865 | 0.464 | 0.000 |
| 3 | 06 | 0.385 | 0.643 | 0.258 | 0.000 |
| 4 | 08 | 0.289 | 0.482 | 0.194 | 0.000 |
| 5 | 24 | 0.468 | 0.801 | 0.333 | 0.123 |
| 6 | 46 | 0.468 | 0.468 | 0.000 | 0.491 |
| 7 | 68 | 0.468 | 0.468 | 0.000 | 0.315 |

$U = 0$ denotes uncertainty-insensitive participants, $U = 1$ sensitive participants.
$n$ denotes number of participants.
$\Delta adr_{med}$ denotes the difference between $U = 1$ and $U = 0$ specific discount rates.

Table 9: Effects of Uncertainty: Median Discount Rates for *incent* Condition

| | $t_1 t_2$ | $U = 0$ (n=133) | $U = 1$ (n=7) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.468 | 1.154 | 0.686 | 0.040 |
| 2 | 04 | 0.401 | 0.965 | 0.564 | 0.007 |
| 3 | 06 | 0.267 | 0.576 | 0.309 | 0.120 |
| 4 | 08 | 0.200 | 0.382 | 0.182 | 0.161 |
| 5 | 24 | 0.152 | 0.801 | 0.649 | 0.050 |
| 6 | 46 | 0.152 | 0.634 | 0.483 | 0.561 |
| 7 | 68 | 0.152 | 0.468 | 0.316 | 0.183 |

$U = 0$ denotes uncertainty-insensitive participants, $U = 1$ sensitive participants, .

$n$ denotes number of participants.

$\Delta adr_{med}$ denotes the difference between $U = 1$ and $U = 0$ specific discount rates.

*Support.* After completion of the experimental tasks, participants were asked whether inherent uncertainty had influenced their choices between sooner and later payments.[20] We constructed a binary variable $U$ from the participants' responses in the following way: $U = 1$ if inherent uncertainty played a role *(sensitive types)* and zero otherwise *(insensitive types)*. 14.06% (27 of 192) of the participants in the *flat* condition and only 5% (7 of 140) of the participants in the *incent* condition stated that inherent uncertainty was an important factor affecting their choices.

Whereas median discount rates of sensitive types differ from median discount rates of insensitive types in both conditions,[21] this difference is only significant for the *flat* group (*p*-values of 0.02 *(flat)* and 0.23 *(incent)* based on a one-sided Wilcoxon rank sum test). The latter result may be due to the small number of sensitive types in the incent condition.

Tables 8 and 9 provide more detailed insights. They list differences in median discount rates for each time tradeoff separately.[22] They reveal quite a consistent pattern for the *flat* condition. For each tradeoff involving the earliest possible payment date (two days, "0"), revealed median discount rates of the *sensitive types* ($U = 1$) are statistically highly significantly larger than those of the *insensitive types* ($U = 0$). Deferring the tradeoffs farther into the future, however, leads to less pronounced and insignificant differences between median dis-

[20]See Appendix D for the exact wording of the question.

[21]78.61% p.a. *(sensitive type)* vs. 46.78% p.a. *(insensitive type)* in the *flat* condition and 96.48% p.a. *(sensitive type)* vs. 28.86% p.a. *(insensitive type)* in the *incent* condition.

[22]Interpretations of the columns are the same as in Table 2. A similar analysis for relative risk premia can be found in Appendix E.

count rates. We do not find such a robust pattern for the *incent* condition in Table 9, although the effects have the same sign.

*Discussion.* The behavioral pattern we find for the group facing hypothetical choices looks quite similar to the *incentive effect* presented above. By and large, both patterns can be described as level effects. The fact that a considerable fraction of excessive discounting of the *flat* group can be explained by inherent uncertainty suggests that such considerations are one central reason for the incentive effect. Put differently, the hypothetical bias may be driven by the fact that the two groups, on average, judge the uncertainty about the materialization of allegedly guaranteed outcomes differently. It seems as if a considerable percentage of the participants confronted with hypothetical choices overestimated the risk of not receiving future rewards. Consequently, we should be able to explain a substantial part of discounting behavior of this group by the hazard they attribute to future outcomes.

One way of modeling this presumed relationship is by allowing the parameters in the *hyperbolic preference model* to vary with participants' perceptions of uncertainty.[23] When we make all the model parameters dependent on the binary indicator $U$, risk preference parameters show no effect. Table 10, therefore, lists the estimation results for the restricted model where only discounting parameters $\eta$ and $\gamma$ are allowed to vary with $U$.

**Result 6 (Hyperbolic Preference Model and Inherent Uncertainty)** *Within the flat group sensitive participants exhibit much higher rates of impatience than do insensitive participants. Within the incent group, however, sensitive participants are not distinguishable from insensitive participants. The sensitive flat participants also exhibit significantly higher impatience than the do the sensitive incent participants, but otherwise treatment groups do not differ significantly on any other dimension of preferences.*

*Support.* The parameter estimates in Table 10 reveal that the effect of $U = 1$ on the level of the rate of time preference, $\eta_U$, amounts to 0.256 for the *flat* group, which constitutes a considerable mark-up on the base rate $\eta_0$ of 0.424. Examining both groups we find that it is the only significant effect of $U$ on parameter values. Moreover, group-specific confidence intervals for hyperbolicity, utility and risk preference parameters overlap.

[23] A different approach, in which perceptions of uncertainty affect discounting behavior via probability weighting, the *hazard rate model*, is presented in Appendix I. This model allows estimating people's subjective probabilities of not receiving future rewards.

Table 10: Hyperbolic Preferences and Inherent Uncertainty

flat

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.111 | 0.036 | 3.069 | 0.002 |
| $\eta_0$ | 0.424 | 0.021 | 19.953 | 0.000 |
| $\eta_U$ | 0.256 | 0.023 | 11.324 | 0.000 |
| $\gamma_0$ | 0.203 | 0.043 | 4.690 | 0.000 |
| $\gamma_U$ | 0.129 | 0.079 | 1.632 | 0.103 |
| $\alpha$ | 0.637 | 0.011 | 60.506 | 0.000 |
| $\beta$ | 0.158 | 0.016 | 10.022 | 0.000 |
| participants | | | | 192 |
| parameters | | | | 9 |
| observations | | | | 8873 |
| $log\mathcal{L}$ | | | | -31276 |

p.e.: parameter estimate, s.e.: standard error.

incent

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.152 | 0.039 | 3.918 | 0.000 |
| $\eta_0$ | 0.364 | 0.021 | 17.418 | 0.000 |
| $\eta_U$ | 0.040 | 0.043 | 0.934 | 0.350 |
| $\gamma_0$ | 0.153 | 0.051 | 3.004 | 0.003 |
| $\gamma_U$ | 0.195 | 0.183 | 1.064 | 0.288 |
| $\alpha$ | 0.630 | 0.012 | 53.177 | 0.000 |
| $\beta$ | 0.167 | 0.017 | 9.700 | 0.000 |
| participants | | | | 140 |
| parameters | | | | 9 |
| observations | | | | 6446 |
| $log\mathcal{L}$ | | | | -22331 |

*Discussion.* Our estimation results indicate that perceived uncertainty indeed boosts discount rates. It is quite puzzling, however, that this effect is operative for a group of people who believe that *experimental earnings* would be quite uncertain even though they responded to purely hypothetical questions. Apparently, people whose choices had real monetary consequences were not troubled by such concerns. A possible explanation is that *incent* people thought harder about the probability of not getting paid, because it made a difference to them whether they would get paid or not, and concluded that it was negligible. However, these findings do not imply that uncertainty inherent in the future does not play a role in real purchase decisions regarding energy-using durables. On the contrary, uncertainty seems to be an important concern, as the next result shows.

Aside from the behavioral data on discounting and risk taking we collected responses to a set of questions relating specifically to energy-using durables. We focused on two types of products people presumably are familiar with: automobiles and cold appliances (refrigerators, freezers). When facing the decision of buying a (new) fridge or car, people report to be concerned not only about product characteristics, such as reliability and service life, but also about uncertain future energy costs:

**Result 7 (Uncertainty and Energy-Using Durables)** *Uncertainty about future energy costs and energy supply are perceived to be important factors in purchase decisions concerning energy-using durables.*

*Support.* To measure the importance of uncertainty about future energy costs and energy supply, we explicitly asked people's assessments in the context of automobile as well as refrigerator purchases (see Appendix F for the question and answers). About 70% of the participants responded that the certainty of future energy costs and energy supply plays an important role when making such decisions.[24]

*Discussion.* Contrary to the comparatively small number of participants who were worried about not receiving their experimental earnings, uncertainty pertaining to future energy costs and supply seems to be an important factor when such a purchase decision has to be made. The estimates of our behavioral model show that future uncertainty may drive up discount

[24]We do not find significant differences in answers between the *flat* and the *incent* condition, which further supports our claim that the incentive effect is not caused by selection.

rates considerably. Therefore, any advantages of lower future running costs of energy-efficient durables may be eroded by uncertainty-boosted discount rates so that their higher investment costs do not pay off. In order to be able to quantify the effect of uncertainty about future energy costs one would need to have data on real purchase decisions collected in the field.

Our estimates have shown that perceptions of future uncertainty may lead to excessive discounting, but they may not be the most important force driving real decisions in the experiment. Presumably, there may be different, potentially more important, factors driving behavior. In order to examine this possibility we take a closer look at results stemming from another experiment.

Recently, we conducted a similar study with university students who got paid in an incentive compatible manner. The discount rates, estimated by the *hyperbolic preference model*, for this subject pool is shown as the gray curve in Figure 2. There is a striking difference between discount rates of our representative groups (red and blue curves) and students: University students exhibit much stronger hyperbolic preferences than the average individual in the population, but in the long run they are more patient. Since there is *a priori* no reason to believe that students should feel more uncertain than other people about being able to collect their experimental earnings, there must be other factors influencing students' behavior which make them highly impatient in the short run.[25] One potential determinant may be students' limited access to financial means. Of course, this argument not only applies to students but also to other socioeconomic groups in the population who may have limited access to capital markets. Therefore, we will extend our analysis to liquidity constraints in order to gain a more complete picture of time discounting.

### 4.4 Results: Liquidity Constraints

People often have limited possibilities of intertemporally allocating quantities of a commodity according to their preferences. There are two main reasons for that being the case. First, the good in question may not be tradable or storable, i.e. there does not exist a market for that particular good. Second, the individual may have only limited access to the market, either

[25] In the context of the hazard rate model, see Appendix I, students would have to perceive the future as much more uncertain than the average person to generate such a strongly hyperbolic decline. However, we estimated students' hazard probability to be roughly 5%, much lower than the 11% found for the uncertainty-sensitive group in our *flat* condition.

because she is excluded from participating in it or because transaction costs are prohibitively large. In what follows, our main focus lies on the second reason, and in particular on liquidity constraints. An individual who has limited access to liquidity, because she holds few liquid assets and cannot borrow against her future labor income, will behave more impatiently than her pure time preferences suggest, simply because there is an immediate need for money now rather than later.

Liquidity constraints seem to be binding for a substantial percentage of the population, not only in developing countries, but also in rich Western countries (Zeldes, 1989; Deaton, 1991). According to the Panel Study of Income Dynamics (`http://psidonline.isr.umich.edu/`), for instance, about 10% of all US households were affected by such constraints before the economic crisis. Without doubt, liquidity constraints may significantly affect household decisions with respect to purchases of energy-consuming durables. To our surprise, however, this potentially important driver of behavior has received only little interest in past research in this field (for an exception see Holden, Shiferaw, and Wik (1998)). To approach this issue, we also asked our participants to state whether they were liquidity-constrained at the time of the experiment. As a proxy for liquidity constraints we used participants' responses to the question whether they were short of cash at the time of the experiment (see Appendix G for more details). We constructed a binary variable $C$ from the participants' responses, such that $C = 1$ if the participant stated that she was liquidity-constrained and zero if she was not.

**Result 8 (Descriptive Results on Liquidity Constraints)** *A minority of participants stated that they were short of cash in the week of the experiment. We find systematic differences between the behaviors of liquidity-constrained and unconstrained participants in both conditions: Liquidity-constrained participants generally exhibit higher discount rates, and this effect is more pronounced in the flat condition.*

*Support.* 12.5% of the participants in the *flat* condition and 8.57% of the participants in the *incent* condition indicated that they were facing liquidity constraints at the time of the experiment, but this difference in percentages is not statistically significant.

Median discount rates of constrained participants differ fundamentally from median discount rates of unconstrained participants in both conditions. These rates amount to 137.92% p.a. *(constrained)* versus 46.78% p.a. *(unconstrained)* in the *flat* condition, and to 43.42% p.a.

Table 11: Effect of Constraints: Median Discount Rates for *flat* Condition

| | $t_1t_2$ | $C = 0$ (n=168) | $C = 1$ (n=24) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.468 | 1.930 | 1.462 | 0.000 |
| 2 | 04 | 0.401 | 1.410 | 1.009 | 0.000 |
| 3 | 06 | 0.267 | 1.289 | 1.022 | 0.000 |
| 4 | 08 | 0.289 | 1.117 | 0.828 | 0.000 |
| 5 | 24 | 0.468 | 1.529 | 1.062 | 0.000 |
| 6 | 46 | 0.468 | 1.154 | 0.686 | 0.000 |
| 7 | 68 | 0.468 | 0.801 | 0.333 | 0.001 |

$C = 0$ denotes unconstrained participants, $C = 1$ constrained participants.
$n$ denotes number of participants.
$\Delta adr_{med}$ denotes the difference between $C = 1$ and $C = 0$ specific discount rates.

Table 12: Effect of Constraints: Median Discount Rates for *incent* Condition

| | $t_1t_2$ | $C = 0$ (n=128) | $C = 1$ (n=12) | $\Delta adr_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 02 | 0.468 | 0.468 | 0.000 | 0.247 |
| 2 | 04 | 0.401 | 0.401 | 0.000 | 0.005 |
| 3 | 06 | 0.267 | 0.385 | 0.118 | 0.001 |
| 4 | 08 | 0.200 | 0.482 | 0.282 | 0.000 |
| 5 | 24 | 0.152 | 0.634 | 0.483 | 0.016 |
| 6 | 46 | 0.152 | 0.634 | 0.483 | 0.016 |
| 7 | 68 | 0.152 | 0.468 | 0.316 | 0.117 |

$C = 0$ denotes unconstrained participants, $C = 1$ constrained participants.
$n$ denotes number of participants.
$\Delta adr_{med}$ denotes the difference between $C = 1$ and $C = 0$ specific discount rates.

*(constrained)* versus 23.39% p.a. *(unconstrained)* in the *incent* condition, and, hence, are about 2.9 *(flat)* and 1.9 *(incent)* times larger for constrained participants than for unconstrained ones. The difference in discount rates is statistically significant in both conditions ($p$-values approximately zero for both the *flat* and the *incent* condition based on a one-sided Wilcoxon rank sum test). Earlier in this report we argued that people are prone to hypothetical bias, i.e. that they exhibit much higher discount rates in the *flat* condition than they do in the *incent* condition. This result is also visible in the rates reported here.

Tables 11 and 12 provide further details. They list differences in median discount rates for each time tradeoff separately. For the *flat* condition the pattern is quite consistent: For all tradeoffs, median discount rates of participants facing constraints ($C = 1$) are significantly larger than the median discount rates of those not facing constraints ($C = 0$). The differences ($\Delta adr_{med}$) between the two groups are substantial (median difference: 1.009). We do not find significant differences for all the tradeoffs in the *incent* condition, however. Nevertheless, the differences show the expected direction of effects.

*Discussion.* Our results suggest that liquidity constraints are one of the key determinants of discounting behavior.[26] Those participants who faced constraints exhibited much larger discount rates in the vast majority of tradeoffs. Possibly even more interestingly, participants confronted with hypothetical choices revealed a much more pronounced reaction to liquidity constraints. We can only speculate about the reasons for the condition-specific sensitivities. A likely explanation may be that, when real money was at stake, people thought more thoroughly about whether being short of cash effectively limited their scope of action, whereas liquidity-constrained *flat* participants may have given in to their initial gut reactions.

What is not clear so far, is what factors are driving this result. Are liquidity-constrained people more risk averse, more impatient or more present biased? To address this question, we employ the behavioral model introduced earlier.

**Result 9 (Hyperbolic Preference Model and Liquidity Constraints)** *Plugging liquidity constraints into our flexible hyperbolic preference model reveals that liquidity-constrained individuals are indeed more impatient than others. In line with our previous results, this effect is more pronounced in the flat condition than in the incent condition.*

*Support.* The parametric results depicted in Table 13 confirm our descriptive findings, but allow us to separate the effect of liquidity constraints on the level of impatience from the effect on hyperbolicity. For both conditions we find that the level of impatience is significantly affected by liquidity constraints. The estimate of $\eta_C$ amounts to 0.551 (*flat*) and 0.146 (*incent*), implying that the constant rates of time preferences for these groups of individuals sum to 95% and 50%, respectively. The estimates for the parameter governing hyperbolicity, $\gamma_C$, are not significantly different from zero in either condition.[27]

[26]Of course, causality could also go the other way: people are liquidity-constrained because they are extremely impatient. In our data, we cannot discriminate between these two alternative hypotheses. However, if this latter explanation were the valid one, the incentive effect would have to be a selection effect. As we argued above, we think that this is highly improbable.

[27]We also estimated a full model with all parameters depending linearly on the constraints dummy $C$. We find no significant effects of constraints on risk preference parameters. Ideally, we would have preferred to include

Table 13: Hyperbolic Preferences and Liquidity Constraints

flat

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.111 | 0.036 | 3.070 | 0.002 |
| $\eta_0$ | 0.402 | 0.020 | 19.972 | 0.000 |
| $\eta_C$ | 0.551 | 0.020 | 27.552 | 0.000 |
| $\gamma_0$ | 0.208 | 0.043 | 4.786 | 0.000 |
| $\gamma_C$ | 0.078 | 0.070 | 1.115 | 0.265 |
| $\alpha$ | 0.637 | 0.011 | 60.505 | 0.000 |
| $\beta$ | 0.158 | 0.016 | 10.023 | 0.000 |
| participants | | | | 192 |
| parameters | | | | 9 |
| observations | | | | 8873 |
| $log\mathcal{L}$ | | | | -31123 |

p.e.: parameter estimate, s.e.: standard error.

incent

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.152 | 0.039 | 3.918 | 0.000 |
| $\eta_0$ | 0.354 | 0.021 | 17.249 | 0.000 |
| $\eta_C$ | 0.146 | 0.035 | 4.222 | 0.000 |
| $\gamma_0$ | 0.172 | 0.053 | 3.264 | 0.001 |
| $\gamma_C$ | -0.054 | 0.140 | -0.388 | 0.698 |
| $\alpha$ | 0.630 | 0.012 | 53.176 | 0.000 |
| $\beta$ | 0.167 | 0.017 | 9.701 | 0.000 |
| participants | | | | 140 |
| parameters | | | | 9 |
| observations | | | | 6446 |
| $log\mathcal{L}$ | | | | -22324 |

*Discussion.* In an earlier study on farmers' discount rates in developing countries, Holden, Shiferaw, and Wik (1998) reported significant effects of liquidity constraints on discounting behavior. Our data is much richer than theirs and allows to explicitly test their conjecture that liquidity constraints induce greater impatience at the level of time preferences. Liquidity constraints indeed raise impatience of *incent* participants by about 40%. The effect of the corresponding *flat* group's rate was much greater, demonstrating again that hypothetical choices and real choices seem to be fundamentally different.

### 4.5 Summary of Experimental Results

We gained four major insights from the experiment: First, we found an unexpected incentive effect. Second, rates of time preference are considerably higher than prevailing market interest rates and exhibit a moderate degree of hyperbolicity. Third, the role of inherent uncertainty in time discounting was confirmed, albeit significantly only for the group of participants who did not get paid for their decisions. Finally, liquidity constraints contribute substantially to high discount rates. In the following, we comment on these findings in detail.

1. A striking result of our experimental study on discounting behavior concerns the magnitude of the effect of monetary incentives on behavior. To our knowledge this is the first evidence on a hypothetical bias in the domain of time discounting for a representative sample. The estimates of the *hyperbolic preference model* have shown that the difference between the *flat* and *incent* groups manifests itself predominantly at the level of impatience: The estimated average rates of constant time preference differ by about 25% or 9 percentage points p.a., as Table 14 reveals. Interestingly, this is the only dimension on which the groups diverge - neither hyperbolicity nor risk preference parameters display an incentive effect. How can we explain this surprising result?

   There is no evidence whatsoever that *flat* participants did not do their best to respond conscientiously and honestly. So it is not time used or effort exerted in the experiment that distinguishes the two groups. Rather, our analysis suggests that differing sensitivities to uncertainty and liquidity constraints are responsible for the incentive effect. Table

both uncertainty and liquidity constraints into the model. Unfortunately, attempts at estimating such a model ran into numerical difficulties, possibly due to the small number of participants with both $C = 1$ and $U = 1$ (*incent*: 1 participant, *flat*: 8 participants).

Table 14: Estimated Rates of Impatience

| | flat | incent |
|---|---|---|
| Average | 45.7% | 36.6% |
| $U = 1$ | 68.0% | 40.4% |
| $C = 1$ | 95.3% | 50.0% |

Constant component of time preference estimated with *hyperbolic preference model*.

14 displays the rates of impatience estimated from the *hyperbolic preference model* for those participants who voiced concerns about the certainty of future payments, $U = 1$, and those who reported to be short of cash, $C = 1$. The *flat* and *incent* groups differ in two respects here: First, with regard to inherent uncertainty, the percentage of subjects in the category $U = 1$ was significantly higher in the *flat* condition than in the *incent* condition (14.06% versus 5%). Second, the rates of impatience estimated for the *flat* group were substantially higher in both categories, $U = 1$ and $C = 1$, but particularly so for the liquidity-constrained individuals. Controlling for uncertainty and liquidity constraints yielded estimates of group-specific preference parameters that were statistically indistinguishable from one another, which underscores that differences in group behavior were mainly driven by these two types of sensitive individuals in the *flat* group.

Even though no real money was at stake, *flat* participants reacted strongly to perceived uncertainty and liquidity constraints and much more so than people who had to make their decisions for real. We interpret this finding as an indication of the intrinsic difficulty of responding to hypothetical questions. Hypothetical surveys, therefore, can at best provide qualitative insights but are not suited to derive any quantitative predictions.

2. According to the *hyperbolic preference model*, the average rate of impatience amounts to approximately 37% p.a., clearly exceeding market interest rates. This result has to be interpreted with reservations, however. First, quantitative estimates depend on the specific model employed. The *hazard rate model*, discussed in Appendix I, attributes some part of people's impatience to the hazard that rewards do not materialize. Consequently, it yields a lower rate of constant time preference, namely 28% p.a. Second, and more importantly, participants' behavior changed over the course of time: *incent* participants

became considerably more patient over the eight months that passed between the first and the second wave of experiments, which resulted in a decline of the estimated rate of impatience by $7-9$ percentage points. We interpret this decline as people's reaction to improved economic conditions after the shock of the financial crisis had subsided. Thus, the rate of time preference seems to be susceptible to factors beyond the experimenters' control. Interestingly, this decline was only observed for people who got paid according to their decisions, whereas people responding to hypothetical questions displayed stable discount rates. This finding strengthens our insights on incentive effects.

As far as hyperbolicity of discount rates is concerned, we found evidence of persistence of present-biased preferences even when we controlled for uncertainty and liquidity constraints. However, the effect of hyperbolicity levels off fairly quickly, as the estimated discount rates in Figure 2 show.[28]

3. Our conjecture that people's doubts about being able to actually collect their future rewards raise discount rates was confirmed. This effect was significant for the *flat* participants and visible, but statistically insignificant, for the *incent* participants. The latter finding is probably due to the small number of people who reported to be concerned about payment. However, even though we are unable to provide a numerical estimate, it is to be expected that uncertainty regarding the consequences of real purchase decisions will indeed increase discount rates considerably. As Kooreman (1995) has shown, ignoring uncertainty with respect to random lifetimes of durables may considerably bias discount rates. He estimated the bias to be as large as 35%.

4. While uncertainty, measured in the context of the experiment, was situation-specific, liquidity constraints are a general feature of a person's financial circumstances. Consequently, the effects of liquidity constraints turned out to be much stronger than the effects of uncertainty and were found for both the *flat* and *incent* groups. If *incent* participants' behavior is taken as standard of reference, liquidity constraints raise discount rates by more than 40%, which may have a substantial impact on real purchase decisions.

[28] In the context of the *hazard rate model*, discussed in Appendix I, hyperbolicity is caused by people's perceptions of uncertainty inherent in the future. The extent of hyperbolic decline can be traced back to a hazard rate of 3‰ p.a., i.e. the probability of receiving rewards due in one year is perceived to be on average 99.97%.

## 4.6 The Role of Information

Consumers' tendency to ignore information about future running costs and their inability to aggregate this information into a meaningful number may be important drivers of the efficiency gap. Studying information problems of this kind is beyond the scope of the current experimental study where participants were fully informed about the consequences of their actions. However, we collected participants' reports of their own perceptions regarding difficulties with judging energy bills for operating automobiles and cold appliances.

**Result 10 (Information Costs)** *Approximately half of the participants report to have problems with assessing monthly energy costs.*

*Support.* Our participants' assessments of information costs with respect to monthly energy bills differ somewhat between automobiles and cold appliances. Table 24 in Appendix F lists the percentages of participants in the different categories of information costs. The percentage of participants with medium to very high information costs is slightly higher for refrigerators than for automobiles, but for both types of products the percentages are in the vicinity of 50%.

*Discussion.* People seem to have problems with assessing the magnitude of monthly energy costs. This result is in line with previous studies. In a survey with 505 participants Attari, DeKay, and Davidson (2010) asked for perceived energy use for a sample of 9 devices and appliances, with the energy used by a 100-Watt incandescent light bulb in one hour provided as reference. On average, participants underestimated energy use by a factor of 2.8. People's perceptions reflected minor overestimates when actual energy use is low and large underestimates when actual use is high.

These findings suggest that improving the public's understanding of energy use could be a successful intervention strategy. However, providing information on energy consumption alone may not suffice. When valuing different investment options, running costs over the lifetime of the product have to be aggregated into a meaningful number, the present value of future costs. As Stango and Ziman (2009) have recently shown, there are systematic biases in household finance: People have a tendency to *ceteris paribus* underestimate interest rates and to underestimate future values. So even if people assessed energy *use* correctly they might not be able to calculate an unbiased present value of their future energy *costs*.

## 5 Policy Implications for Energy-Using Durables

The focus of our research is individual discounting behavior and how it may affect investment decisions regarding energy-using durables. Observed discount rates are typically much higher than market interest rates, which suggests that people underweight cost savings in the future and focus on the purchase price when buying a new product. Several factors potentially contribute to this underweighting of future cost savings:

1. High individual rates of pure time preference, often coupled with present bias (hyperbolic discounting)

2. Uncertainty regarding service life, reliability and future energy costs

3. Liquidity constraints and limited access to capital markets

4. Difficulties with obtaining and processing information concerning future running costs

The choice of the right policy instrument crucially depends on the underlying cause of high discount rates. Therefore, it was the objective of our project to separate the effects of pure time preferences from other factors influencing discounting behavior. Our experimental data enabled us to examine the effects of inherent uncertainty and liquidity constraints. The importance of information problems was assessed by specific questions in the questionnaire. We will discuss each of these factors in more detail below.

1. **Time preferences**

   In the empirical literature, the measurement of time preferences has been plagued by many confounds, such as hypothetical bias, utility curvature and uncertainty (Frederick, Loewenstein, and O'Donoghue, 2002). Controlling for these potential confounds in our analysis renders estimates of the rate of time preference that lie, depending on the model, in the vicinity of 30% p.a. As discussed in Section 4.5, this number should not be interpreted as the universal true rate, however. People's rates of time preference seem to be malleable, possibly depending on the state of the overall economy.

   If people prefer to put little weight on future outcomes, launching an education campaign - and probably even worse, launching a campaign during an economic crisis -

will most likely not alter their behavior. In such a case, direct incentives have to be provided that change people's cost-effectiveness calculations. The relative weights of purchase price and future running costs can, in principle, be influenced by changing relative prices of high- and low-efficiency poducts, by withdrawing inefficient products from the market, or by increasing energy costs.

A different problem arises when high energy efficiency is bundled with other premium product attributes, such as a "better" brand and higher reliability, which seems to be the case particularly in some white goods markets (DEFRA, 2010). In those markets the additional upfront investment is disproportionately large, which may impede the uptake of the very best energy performance even when consumers optimize their investment decisions. In this case, policy could encourage manufactures to offer high-efficiency products without additional luxury attributes.

As far as hyperbolicity of discount rates is concerned, we found evidence of persistence of present-biased preferences even when we controlled for uncertainty and liquidity constraints. Due to hyperbolicity, average discount rates are higher than the rates of constant time preference and decline over time. Hyperbolic discounting produces procrastination and oversensitivity to immediate costs and benefits. Oversensitivity to the immediate costs of acquiring energy-using durables can be attenuated by changing the nature of the transaction: Rather than buying the product itself the consumer could buy the product's stream of services or enter into a leasing contract.

Procrastination can be relevant to the timing of many energy related decisions, such as installing insulation, replacing inefficient light bulbs, or buying a new refrigerator. In fact, our participants mentioned as one of the main motives for buying a new automobile or refrigerator the replacement of a broken one or of one no longer tailored to their needs. Replacing appliances because they have become inefficient seems to be not on the surface of consumers' awareness. Policies, such as subsidies for the scrappage of old cars, that nudge consumers to bring forward their investments in high-efficiency products may counteract present-biased preferences (Nemry, Vanherle, Zimmer, Uihlein, Genty, Rueda-Cantuche, Mongelli, Neuwahl, Delgado, Hacker, Seum, Buchert, and Schade, 2009).

2. **Uncertainty**

   Our research has shown that discount rates may be considerably higher for people who feel uncertain about future outcomes. In the context of energy-using durables uncertainty may pertain to product lifetime and reliability as well as to future running costs. Uncertainty *per se* should not interfere with the optimality of decisions, however, when risk-adjusted discount rates are used in consumers' cost-effectiveness calculations. High-efficiency products with comparatively high service reliability should even have an advantage on this count and be effectively associated with lower discount rates than are low-efficiency products. Moreover, in many markets for energy-using durables retailers offer warranties and service contracts that cover these contingencies.

3. **Liquidity Constraints**

   According to our estimates, liquidity-constrained individuals exhibit rates of impatience that are about 40% higher than the corresponding rates of unconstrained individuals. Therefore, investments in high-efficiency durables may not be profitable for consumers facing high borrowing rates on the market. But liquidity constraints may be an obstacle to buying any durable product be it energy-efficient or not. As in the case of uncertainty, private initiative has provided a solution to this problem: Customers with limited financial means often finance their purchases of durables by payment in installments, typically offered by the retailer, or by leasing the product instead of owning it. Sometimes the purchase contract even offers postponement of the first installment payment by several months, which also cushions oversensitivity to immediate costs caused by present-biased preferences.

4. **Information**

   In our experiment, information costs were largely absent. Participants were fully informed about the financial consequences of their actions, they knew the exact monetary amounts and the dates payment was due and, therefore, costs of obtaining and processing information could not have manifested themselves in individuals' discount rates in the experiment. In the context of purchase decisions regarding energy-using durables, information costs may be considerable. As we have argued above, many potential biases affect the process of evaluation of future running costs: Consumers may have problems with estimating monthly energy use and corresponding costs as well as with integrating these costs into a meaningful number they can compare with upfront outlays. These biases may lead to suboptimal choices and, therefore, constitute a justification for policy intervention in its own right.

Making running costs more salient to the consumers may help shift their attention to potential cost savings from buying high-efficiency appliances. The challenge here is to find the right format. Simply providing labels that reveal the product's energy consumption class will probably not suffice. In Japan, for instance, energy labels also display the expected annual electricity bill, which may assist consumers in their choices. Alternatively, one could provide information on the break-even point. Recently, Deutsch (2007) conducted a field experiment by disclosing lifecycle costs of cooling appliances and washing machines in two major German commercial websites. His analysis of click-stream data of consumers' shopping behavior suggests that lifetime cost disclosure reduces the energy use of the chosen products. Estimates of lifetime costs are based on a number of assumptions, such as actual usage patterns. Interactive tools that enable consumers to calculate their own long run costs could provide consumers with salient information. These interactive tools could be supplied by the retailer at the point of sale or by price comparison websites.

Some commentators identify bounded rationality as the major cause of excessive discount rates but argue that better information and education will most likely not suffice to remedy consumers' misoptimization. Consequently, public policy should intervene by changing relative prices of high-efficiency and low-efficiency products. In this context, the concept of so-called feebates, a combination of fees (taxes) and rebates, has recently attracted attention both from academic researchers and the European Commission (Nemry, Vanherle, Zimmer, Uihlein, Genty, Rueda-Cantuche, Mongelli, Neuwahl, Delgado, Hacker, Seum, Buchert, and Schade, 2009). In an elaborate study of the U.S. automobile market Allcott and Wozny (2010) examine such a policy that imposes sales taxes increasing in a vehicle's expected future fuel consumption while rebating a fixed amount calibrated such that the aggregate market share of new vehicles remains unchanged. Their calculations show that such a policy could result in consumers' welfare gains that exceed the welfare gains from reducing negative externalities.

In principle, the idea of feebates can also be adopted to change transaction features other than the relative prices of energy-using durables. For instance, charges for warranties and service contracts can be made dependent on the relative efficiency of the product. A more radical solution could be to forbid retailers to offer warranty and service contracts for low-efficiency products altogether. In the same vein, feebates could be used to mitigate consequences of liquidity constraints by subsidizing installment sales and leasing contracts for high-efficiency products and penalizing low-efficiency ones. We suspect that, at least private lessees, would refrain from leasing luxury cars with high fuel consumption if leasing rates were sufficiently high.

Policy measures such as feebates constitute far-reaching interventions. In order to avoid any unintended welfare effects the policy maker has to make sure that her decisions are based on correct assumptions concerning the extent of undervaluation of future costs. In our view, there are several concerns that have to be resolved before policy makers set out to implement incisive measures. Our study has offered new insights on people's discounting behavior, but it has also raised new questions. In particular, our hypothesis that general economic conditions impact discounting behavior should become a topic of future research.

Another important issue that we have barely touched upon is heterogeneity both of consumers and product markets. Market outcomes depend on the distribution of different types of consumers as well as on specific product attributes. Therefore, discount rates should be estimated on a market-by-market basis. The majority of studies on implicit discount rates inferred from real purchase decisions were conducted in the 1970's and 1980's in the US. To our knowledge, comparable data for energy-using durables in Switzerland is missing. It would be a worthwhile endeavor to study consumers' choices of energy-using durables at the point of sale, either at retailers' locations or webshops, and to collect socio-demographic data to make further progress on measuring time preferences and the heterogeneity of consumers.

# Appendix

## A Socioeconomic Structure of Samples

Table 15 depicts the fractions of participants in each socioeconomic category (number of participants listed in parentheses).

Table 15: Socioeconomic Characteristics Wave 1

| gender | employment status | age class | quota | flat | incent |
|---|---|---|---|---|---|
| males | employed | 15-30 years | 7.100% | 4.688% (9) | 6.429% (9) |
| | | 31-50 years | 21.800% | 22.917% (44) | 20.714% (29) |
| | | 51-74 years | 9.300% | 9.896% (19) | 7.143% (10) |
| males | unemployed | 15-30 years | 8.000% | 7.292% (14) | 7.857% (11) |
| | | 31-50 years | 1.300% | 0.521% (1) | 1.429% (2) |
| | | 51-74 years | 5.600% | 6.250% (12) | 6.429% (9) |
| females | employed | 15-30 years | 5.700% | 8.854% (17) | 9.286% (13) |
| | | 31-50 years | 17.500% | 25.000% (48) | 23.571% (33) |
| | | 51-74 years | 6.200% | 3.125% (6) | 8.571% (12) |
| females | unemployed | 15-30 years | 8.700% | 5.729% (11) | 5.714% (8) |
| | | 31-50 years | 5.200% | 3.125% (6) | 0.714% (1) |
| | | 51-74 years | 3.600% | 2.604% (5) | 2.143% (3) |

Table 16: Socioeconomic Characteristics Wave 2

| gender | employment status | age class | quota | flat | incent |
|---|---|---|---|---|---|
| males | employed | 15-30 years | 7.100% | 1.875% (3) | 7.018% (8) |
| | | 31-50 years | 21.800% | 23.750% (38) | 19.298% (22) |
| | | 51-74 years | 9.300% | 11.875% (19) | 10.526% (12) |
| males | unemployed | 15-30 years | 8.000% | 8.750% (14) | 7.895% (9) |
| | | 31-50 years | 1.300% | 0.000% (0) | 0.877% (1) |
| | | 51-74 years | 5.600% | 6.875% (11) | 5.263% (6) |
| females | employed | 15-30 years | 5.700% | 3.750% (6) | 7.895% (9) |
| | | 31-50 years | 17.500% | 27.500% (44) | 21.930% (25) |
| | | 51-74 years | 6.200% | 4.375% (7) | 9.649% (11) |
| females | unemployed | 15-30 years | 8.700% | 7.500% (12) | 6.140% (7) |
| | | 31-50 years | 5.200% | 1.875% (3) | 0.877% (1) |
| | | 51-74 years | 3.600% | 1.875% (3) | 2.632% (3) |

# B Choice Menus

Figure 3: Typical Choice Menu for Time Task

| | Option A<br>in 2 Tagen | Ihre Wahl | Option B<br>in 4 Monaten |
|---|---|---|---|
| 0 | CHF 60 | A ⊙ ○ B | |
| 1 | CHF 57 | A ⊙ ○ B | |
| 2 | CHF 54 | A ⊙ ○ B | |
| 3 | CHF 51 | A ⊙ ○ B | |
| 4 | CHF 48 | A ⊙ ○ B | |
| 5 | CHF 45 | A ⊙ ○ B | |
| 6 | CHF 42 | A ⊙ ○ B | |
| 7 | CHF 39 | A ○ ⊙ B | |
| 8 | CHF 36 | A ○ ⊙ B | |
| 9 | CHF 33 | A ○ ⊙ B | |
| 10 | CHF 30 | A ○ ⊙ B | CHF 60 |
| 11 | CHF 27 | A ○ ⊙ B | |
| 12 | CHF 24 | A ○ ⊙ B | |
| 13 | CHF 21 | A ○ ⊙ B | |
| 14 | CHF 18 | A ○ ⊙ B | |
| 15 | CHF 15 | A ○ ⊙ B | |
| 16 | CHF 12 | A ○ ⊙ B | |
| 17 | CHF 9 | A ○ ⊙ B | |
| 18 | CHF 6 | A ○ ⊙ B | |
| 19 | CHF 3 | A ○ ⊙ B | |
| 20 | CHF 0 | A ○ ⊙ B | |

Figure 4: Typical Choice Menu for Risk Task

| | Option A garantierter Gewinn | Ihre Wahl | Option B unsicherer Gewinn |
|---|---|---|---|
| 0 | CHF 60 | A ⊙ ○ B | Gewinn von CHF 60 in 25% aller Fälle<br><br>und Gewinn von CHF 20 in 75% aller Fälle |
| 1 | CHF 58 | A ⊙ ○ B | |
| 2 | CHF 56 | A ⊙ ○ B | |
| 3 | CHF 54 | A ⊙ ○ B | |
| 4 | CHF 52 | A ⊙ ○ B | |
| 5 | CHF 50 | A ○ ⊙ B | |
| 6 | CHF 48 | A ○ ⊙ B | |
| 7 | CHF 46 | A ○ ⊙ B | |
| 8 | CHF 44 | A ○ ⊙ B | |
| 9 | CHF 42 | A ○ ⊙ B | |
| 10 | CHF 40 | A ○ ⊙ B | |
| 11 | CHF 38 | A ○ ⊙ B | |
| 12 | CHF 36 | A ○ ⊙ B | |
| 13 | CHF 34 | A ○ ⊙ B | |
| 14 | CHF 32 | A ○ ⊙ B | |
| 15 | CHF 30 | A ○ ⊙ B | |
| 16 | CHF 28 | A ○ ⊙ B | |
| 17 | CHF 26 | A ○ ⊙ B | |
| 18 | CHF 24 | A ○ ⊙ B | |
| 19 | CHF 22 | A ○ ⊙ B | |
| 20 | CHF 20 | A ○ ⊙ B | |

# C Temporal Stability of Risk Preferences

Tests are based on a two-sided Wilcoxon rank-sum test.

Table 17: Median Relative Risk Premia by Probability for *flat* Condition

| | $\overline{p}$ | wave1 (n=160) | wave2 (n=160) | $\Delta rrp_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 0.05 | -0.167 | -0.167 | 0.000 | 0.371 |
| 2 | 0.10 | -0.137 | -0.159 | -0.022 | 0.048 |
| 3 | 0.25 | -0.056 | -0.056 | 0.000 | 0.345 |
| 4 | 0.50 | 0.017 | 0.030 | 0.013 | 0.730 |
| 5 | 0.75 | 0.082 | 0.082 | 0.000 | 0.313 |
| 6 | 0.90 | 0.071 | 0.083 | 0.013 | 0.290 |
| 7 | 0.95 | 0.090 | 0.115 | 0.026 | 0.048 |

Table 18: Median Relative Risk Premia by Probability for *incent* Condition

| | $\overline{p}$ | wave1 (n=114) | wave2 (n=114) | $\Delta rrp_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 0.05 | -0.167 | -0.167 | 0.000 | 0.059 |
| 2 | 0.10 | -0.159 | -0.205 | -0.045 | 0.000 |
| 3 | 0.25 | -0.060 | -0.100 | -0.040 | 0.372 |
| 4 | 0.50 | 0.030 | 0.017 | -0.013 | 0.031 |
| 5 | 0.75 | 0.100 | 0.082 | -0.018 | 0.119 |
| 6 | 0.90 | 0.083 | 0.083 | 0.000 | 0.591 |
| 7 | 0.95 | 0.090 | 0.115 | 0.026 | 0.120 |

## D Sources of Uncertainty

Question: "Which of the following factors influenced your choices between sooner and later payments?"

Response items pertaining to four different sources (in italics):[29]

- *participant:* For some reason it may be impossible for me to obtain the money.
- *mailing:* It is possible that the money will not be delivered.
- *experimenters:* The survey organizers are not trustworthy.
- *other factors:* Other, non-influenceable reasons.

There were five different response categories: *clearly yes*, *rather yes*, *rather not*, *not at all*, and *don't know*. Participants had to choose one of these categories for each of the four items. Participants' responses are shown in Table 19 below.

Our analysis in the empirical part of this paper only use the first item *(participant)*. There are a number of reasons for this. First, we believe that this question reproduces best the idea behind inherent uncertainty, i.e. the subjective risk of not receiving the reward. Second, the two sources of uncertainty *mailing* and *experimenters* seem to have played a minor role. We cannot use these variables as we do not have a sufficient number of observations for some of the response categories. Finally, we have reasons to believe that participants did not attribute *other factors* to uncertainty only.

Furthermore, to have a sufficient number of observations in each category and keep our analysis as concise as possible, we constructed a binary variable $U$ indicating whether subjective uncertainty played a role in the individual's choices. This variable $U$ is equal to one if the individual stated that subjective uncertainty is relevant when making intertemporal choices (*rather yes* or *clearly yes*) and zero otherwise (*rather not*, *not at all*, or *don't know*).

[29]We only present the exact wording of the *incent* condition. Questions were the same for the *flat* condition, but used subjunctive rather than indicative mode.

Table 19: Sources of Uncertainty

| item | condition | not at all | rather not | don't know | rather yes | clearly yes |
|---|---|---|---|---|---|---|
| *participant* | flat | 61.458% | 17.188% | 7.292% | 13.021% | 1.042% |
| | incent | 70.000% | 19.286% | 5.714% | 4.286% | 0.714% |
| *mailing* | flat | 57.292% | 30.208% | 5.729% | 5.729% | 1.042% |
| | incent | 65.000% | 24.286% | 6.429% | 3.571% | 0.714% |
| *experimenters* | flat | 63.542% | 22.917% | 11.458% | 1.042% | 1.042% |
| | incent | 73.571% | 18.571% | 5.000% | 2.143% | 0.714% |
| *other factors* | flat | 48.958% | 18.229% | 18.750% | 11.979% | 2.083% |
| | incent | 49.286% | 17.143% | 20.000% | 11.429% | 2.143% |

# E Inherent Uncertainty and Relative Risk Premia

Table 20: Median Relative Risk Premia by Tradeoff for *flat* Condition

| | $\overline{p}$ | $U = 0$ | U = 1 | $\Delta rrp_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 0.05 | -0.167 | -0.190 | -0.024 | 0.199 |
| 2 | 0.10 | -0.159 | -0.185 | -0.026 | 0.704 |
| 3 | 0.25 | -0.056 | -0.100 | -0.044 | 0.192 |
| 4 | 0.50 | 0.017 | 0.017 | 0.000 | 0.112 |
| 5 | 0.75 | 0.082 | 0.100 | 0.018 | 0.932 |
| 6 | 0.90 | 0.083 | 0.109 | 0.026 | 0.284 |
| 7 | 0.95 | 0.090 | 0.121 | 0.031 | 0.156 |

Table 21: Median Relative Risk Premia by Tradeoff for *incent* Condition

| | $\overline{p}$ | $U = 0$ | U = 1 | $\Delta rrp_{med}$ | $p$-value |
|---|---|---|---|---|---|
| 1 | 0.05 | -0.167 | -0.238 | -0.071 | 0.622 |
| 2 | 0.10 | -0.159 | -0.136 | 0.023 | 0.880 |
| 3 | 0.25 | -0.060 | -0.038 | 0.022 | 0.347 |
| 4 | 0.50 | 0.030 | 0.050 | 0.020 | 0.452 |
| 5 | 0.75 | 0.100 | 0.140 | 0.040 | 0.412 |
| 6 | 0.90 | 0.083 | 0.075 | -0.009 | 0.998 |
| 7 | 0.95 | 0.090 | 0.115 | 0.026 | 0.711 |

# F Energy-Using Durables: Uncertainty and Information Costs

Question: "For your past or future purchases of automobiles (refrigerators), how important are the following factors in comparison to the purchase price?"

Table 22: Automobiles

| factor | condition | plays no role | unimportant | don't know | important | very important |
|---|---|---|---|---|---|---|
| *reliability* | flat | 0.521% | 1.042% | 1.562% | 26.562% | 70.312% |
| | incent | 0.714% | 2.857% | 0.000% | 31.429% | 65.000% |
| *fuel costs* | flat | 1.042% | 8.333% | 1.562% | 32.812% | 56.250% |
| | incent | 0.714% | 8.571% | 0.000% | 40.000% | 50.714% |
| *certainty of future fuel supply* | flat | 3.646% | 19.271% | 5.208% | 44.271% | 27.604% |
| | incent | 5.000% | 22.857% | 4.286% | 41.429% | 26.429% |
| *certainty of future fuel costs* | flat | 2.604% | 17.188% | 5.208% | 42.708% | 32.292% |
| | incent | 3.571% | 21.429% | 6.429% | 44.286% | 24.286% |



Table 23: Refrigerators

| factor | condition | plays no role | unimportant | don't know | important | very important |
|---|---|---|---|---|---|---|
| *reliability* | flat | 0.521% | 3.125% | 0.521% | 23.438% | 72.396% |
| | incent | 0.714% | 2.143% | 0.000% | 37.857% | 59.286% |
| *energy costs* | flat | 1.562% | 2.604% | 1.042% | 24.479% | 70.312% |
| | incent | 0.000% | 7.857% | 0.714% | 33.571% | 57.857% |
| *certainty of future energy supply* | flat | 5.729% | 14.583% | 4.688% | 39.583% | 35.417% |
| | incent | 7.857% | 22.143% | 6.429% | 35.714% | 27.857% |
| *certainty of future energy costs* | flat | 6.250% | 14.062% | 6.250% | 39.062% | 34.375% |
| | incent | 5.000% | 22.143% | 4.286% | 37.143% | 31.429% |

Question: “How costly do you think is information acquisition concerning monthly fuel bills (energy costs)?”

Table 24: Information Costs

| factor | condition | very low | low | medium | high | very high |
|---|---|---|---|---|---|---|
| *automobiles* | flat | 47.396% | 6.250% | 23.958% | 21.354% | 1.042% |
| | incent | 42.857% | 7.857% | 28.571% | 20.000% | 0.714% |
| *refrigerators* | flat | 39.062% | 10.417% | 35.417% | 14.062% | 1.042% |
| | incent | 35.000% | 10.714% | 41.429% | 10.714% | 2.143% |

## G Liquidity Constraints

Questionnaire Item: "I am short of cash this week."

There were five different response categories: *clearly yes*, *rather yes*, *rather not*, *not at all*, and *don't know*. Participants had to choose one of these categories. Their responses are shown in Table 25 below.[30]

To have sufficient number of observations in each category and keep our analysis as concise as possible, we constructed a binary variable $C$ indicating whether the participant was constrained at the time of the experiment. This variable $C$ is equal to one if the individual stated that she is constrained (*rather yes* or *clearly yes*) and zero otherwise (*rather not*, *not at all* or *don't know*).

Table 25: Liquidity Constraints

| condition | not at all | rather not | don't know | rather yes | clearly yes |
|---|---|---|---|---|---|
| flat | 58.854% | 24.479% | 4.167% | 7.812% | 4.688% |
| incent | 65.714% | 22.143% | 3.571% | 6.429% | 2.143% |

[30] We posed the same question in the *incent* and the *flat* condition.

# H Econometric Specification

In this section, we present the econometric specification used for structural estimation of the *hyperbolic preference model*. Besides the intuitions provided earlier, we need a number of additional assumptions to make the model operational and identifiable. In particular, we motivate our approach to account for diminishing marginal utility and present our assumptions on functional forms and error specifications. Our model consists of two components: A *discounting model* and a *risk model*. We are mainly interested in time discounting and use the risk data to allow identification of the concavity of the utility function.

We introduced the general *discounting model* in Section 3 (see Equation 1). In the experiment, we elicited the smaller sooner amount $x_1$ at $t_1$ that made participants indifferent to a given larger later amount $x_2$ at $t_2$. The smaller sooner amount $\hat{x}_{1k}$ for a particular decision situation $k \in \{1, ..., K\}$ can be written as

$$\hat{x}_{1k} = u^{(-1)} \left[ \frac{d(t_{2k})}{d(t_{1k})} u(x_{2k}) \right] , \tag{3}$$

where $d$ denotes the discount function and $u$ denotes the utility of monetary payoffs $x$.

For modeling $d$, we use a function nesting constant time preferences, but flexible enough to capture hyperbolic time preferences as well. The function proposed by Bleichrodt, Rohde, and Wakker (2009) allows for constant, decreasing and increasing impatience.[31] We specify

$$d(t) = \begin{cases} e^{-\eta t^{1-\gamma}} & \text{if } \gamma < 1 \\ t^{-\eta} & \text{if } \gamma = 1 \\ e^{\eta t^{1-\gamma}} & \text{if } \gamma > 1 \end{cases} , \tag{4}$$

where $\eta$ reflects the level of impatience, and $\gamma$ captures how impatience evolves over time.[32] For $\gamma = 0$, $\eta$ is equal to a continuously compounded discount rate and $d$ takes on the typical exponential form. For $\gamma > 0$ ($\gamma < 0$) the function exhibits discount rates decreasing (increasing) in time horizon.[33]

[31] A subset of this specification of the discount function was originally introduced by Prelec (2004).

[32] Note that for the latter two cases the function is only defined for $t > 0$. However, this poses no problem here as the earliest payment date was two days after completion of the experiment.

[33] $\frac{\gamma}{t}$ corresponds to the Pratt-Arrow convexity of the logarithm of the discount function, $\gamma = -t \frac{[\ln(d(t))]''}{[\ln(d(t))]'}$, a measure for departures from stationarity (see Prelec (1989, 2004)).

Note that the utility function cannot be identified using the data from the time discounting task alone, as there are infinitely many combinations of the rate of time preference and the index of concavity of the utility function fulfilling Equation 3. We therefore need a suitable procedure to control for nonlinear utility.

To do that, we use the risk data. The choice of our *risk model* is motivated by the empirical literature on decision making in this domain (see e.g. Starmer (2000)). We employ a rank-dependent utility model (Quiggin, 1982) capturing both, preferences nonlinear in outcomes and preferences nonlinear in probabilities. This allows decomposing observed risk attitudes into its two components, marginal utility and probabilistic risk aversion. Wakker (1994) motivates this idea by arguing that "utility should describe an intrinsic appreciation of money, prior to probabilities or risk" (p.3). In other words, our instantaneous utility function captures participants' preferences over monetary outcomes, which we assume to be identical in both decision domains. Accounting for such preferences is of particular importance, as the concavity of the utility function can seriously confound measurement of discount rates. When not doing so, one may significantly overestimate the level of impatience as well as its decrease over time.

In the risk task, we observed certainty equivalents . Following rank-dependent utility theory, the certainty equivalent $\hat{y}_l$ for a particular prospect $l \in \{1, ..., L\}$ is equal to

$$\hat{y}_l = u^{(-1)} \left[ w(\overline{p}_l) u(\overline{x}_l) + (1 - w(\overline{p}_l)) u(\underline{x}_l) \right] , \tag{5}$$

where $\overline{x}_l > \underline{x}_l$, and $w$ denotes the probability weighting function. Since participants were confronted with prospects over two nonzero outcomes, the utility function $u$ is identifiable. We can jointly estimate the two parts of the model defined in Equations 3 and 5 to control for diminishing marginal utility in time discounting.

We use a power-specification for the instantaneous utility function $u$ (Pratt, 1964).[34] It has

[34]See Wakker (2008) for a recent discussion.

the following form:[35]

$$u(x) = \begin{cases} x^{1-\rho} & \text{if } \rho < 1 \\ \ln x & \text{if } \rho = 1 \\ -x^{1-\rho} & \text{if } \rho > 1 \end{cases}, \tag{6}$$

where concavity is solely captured by $\rho$, with $\frac{\rho}{x}$ being the Arrow-Pratt index of concavity. For $\rho > 0$ ($\rho < 0$) the function is concave (convex). $\rho = 0$ reflects the special case where utility is linear in outcomes. Utility $u$ links Equations 3 and 5.

A potential problem when using such an approach to account for nonlinear utility may be that risk attitudes are not solely driven by the curvature of the instantaneous utility function. Rather, participants may systematically under- or overweight probabilities. Neglecting this source of risk attitudes would lead to biased estimates of the curvature parameter $\rho$. Our data is rich enough to separate these two effects. We control for probability weighting by using the following two-parameter function (Prelec, 1998):

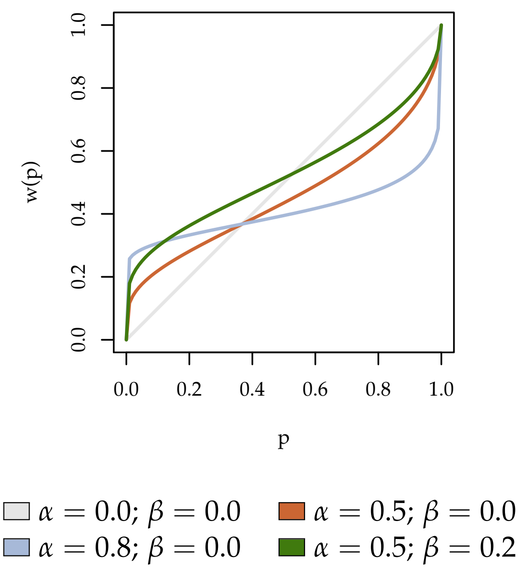
$$w(p) = e^{-(1-\beta)(-\ln p)^{1-\alpha}} \tag{7}$$

In this specification, $\alpha$ denotes an index for curvature, where the function is inversely S-shaped for $\alpha > 0$. Higher values correspond to stronger departures from linear probability weighting ($\alpha = 0$). On the other hand, $\beta$ largely governs the elevation of the curve. More risk proneness is associated with larger, positive $\beta$'s, where the function intersects the identity line at $p = 1/e \approx 0.37$ for $\beta = 0$. Figure 5 plots exemplary curves for four different configurations of parameter values.

The base *hyperbolic preference model* describes the behavior of an average individual by its utility, discounting and risk parameters $\rho, \eta, \gamma, \alpha, \beta$. When we examine the effect of inherent uncertainty or liquidity constraints on time discounting, we are interested in the average behavior of specific subgroups of the population who are either sensitive to uncertainty inherent in the future or liquidity constrained. For this purpose, we define binary variables $U$ and $C$ by setting $U = 1$ if the individual expresses doubts about the certainty of payment and zero otherwise, and $C = 1$ if the individual reports to be short of cash and zero otherwise. The

[35]Note that $\ln x$ is not defined for $x = 0$. Therefore, estimation is carried out after shifting all outcomes by $1E-10$.

Figure 5: Probability Weighting Function for Various Parameter Values




behavioral parameters $\theta \in \{\rho, \eta, \gamma, \alpha, \beta\}$ are then assumed to depend linearly on $X \in \{U, C\}$, such that $\theta = \theta_0 + \theta_X \times X$. $\theta_0$ measures average behavior overall, whereas $\theta_X$ indicates to what extent people with the characteristic $X = 1$ deviate from average behavior. Therefore, the sum of $\theta_0 + \theta_X$ measures their group-specific behavior.

So far, our model only explains deterministic choice. However, people may commit errors for various reasons, such as carelessness, hurry or inattentiveness, resulting in accidentally wrong answers (Hey and Orme, 1994). As a consequence, the actual indifference amounts are bound to deviate from predicted indifference amounts by an error. That is, an individual $i$ reports $x_{1ik} = \hat{x}_{1k} + \epsilon_{ik}$ (in the time discounting task) and $y_{il} = \hat{y}_l + v_{il}$ (in the risk taking task). We assume that the error terms are independent across each individuals' choices and normally distributed.

We allow for two different sources of heteroskedasticity in the error variance. First, for each choice, participants had to consider 21 candidate outcomes, which are equally spaced throughout the prospect's range $x_{2k}$ (for intertemporal choices) and $\overline{x}_l - \underline{x}_l$ (for risky choices), respectively. Since the observed equivalents are calculated as the arithmetic mean of the smallest earlier (certain) amount preferred to the temporal (risky) prospect and the subsequent amount of the list, the error is proportional to the prospect range. Second, evaluation of temporal prospects may be differently affected by error proneness than the evaluation of risky prospects. Therefore, we allow for task-specific variances in the error term. This yields the form $\tau_k = \xi x_k$ for the time task and $\sigma_l = \nu(\overline{x}_l - \underline{x}_l)$ for the risk task for the standard deviation of the error term distribution, where $\xi$ and $\nu$ denote the task-specific parameters.

Having discussed all the necessary ingredients, we now turn to model specification. We are interested in the parameter vector $\theta = (\eta, \rho, \chi, \alpha, \beta)'$, where $\theta^{(T)}$ and $\theta^{(R)}$ extracts the relevant parameters of the time and risk equation from the vector $\theta$, respectively, and $\chi$ either consists of $\gamma$, in case of the base *hyperbolic preference model*, $\gamma_0$ and $\gamma_X$ in case of the extended versions where their parameters depend on the binary variable $X \in \{U, C\}$. Given our assumptions on the distribution of the error term, the density for the $i$-th individual can be expressed as

$$f(x_{1i}, \mathcal{T}; \theta^{(T)}, \xi) = \prod_{k=1}^{K} \tau_k^{-1} \phi \left( \frac{x_{1ik} - \hat{x}_{1k}}{\tau_k} \right) \tag{8}$$

for the time discounting task, and

$$g(y_i, \mathcal{R}; \theta^{(R)}, \nu) = \prod_{l=1}^{L} \sigma_l^{-1} \phi \left( \frac{y_{il} - \hat{y}_l}{\sigma_l} \right) \tag{9}$$

for the risk taking task, where $\phi(\cdot)$ denotes the density of the standard normal distribution. The log-likelihood of the model is then given by

$$\ln \mathcal{L}\left(\theta; x_1, y, \mathcal{T}, \mathcal{R}\right) = \sum_{i=1}^{N} \left( \ln f(x_{1i}, \mathcal{T}; \theta^{(T)}, \xi) + \ln g(y_i, \mathcal{R}; \theta^{(R)}, \nu) \right). \tag{10}$$

The parameters are estimated by maximizing $\ln \mathcal{L}(\cdot)$ with respect to $\theta$ using a standard quasi-Newton method. We do this for each condition (*flat* and *incent*) separately, which allows a comparison and interpretation of treatment differences. Standard errors are derived from the observed Fisher information matrix.

# I The Hazard Rate Model

A different approach to modeling discounting behavior explicitly builds on the idea that the future is inherently uncertain. If this is the case people's risk preferences must also play a role in time discounting. One of the most robust empirical findings on risk taking behavior is people's proneness to probability distortion, i.e. the majority of people's decisions can best be explained by a risk taking model that accounts for nonlinear probability weighting $w$ (see the survey by (Starmer, 2000)). We now assume that the probability that "something may go wrong", the hazard probability $\lambda$, will also be subjectively weighted, yielding an additional discount factor $w((1-\lambda)^t)$ to the exponential one. In total the discount function then amounts to

$$d(t) = e^{-\eta t} w((1-\lambda)^t). \tag{11}$$

Therefore, probability distortions also affect discounting behavior. It can be shown theoretically that, under specific conditions, the resulting discount function declines hyperbolically, i.e. at a decreasing rate (Halevy, 2008; Epper, Fehr-Duda, and Bruhin, 2010). This specification is quite flexible as it also allows for exponential discounting if $w$ is linear.[36]

Even though the *hyperbolic preference model*, discussed above, can be augmented with additional variables it is still a descriptive tool and not based on an underlying theory of behavior. This is not the case for the *hazard rate model*, which imposes structural relationships derived from theory on the variables of interest. In the following, we present estimates of this structural approach which pins down differences in behavior on diverging perceptions of uncertainty. The hazard rate $\lambda$ is assumed to depend linearly on the binary variable $U$, indicating uncertainty-sensitivity, such that $\lambda = \lambda_0 + \lambda_U \times U$.

**Result 11 (Hazard Rate Model)** *Estimation results for the hazard rate model indicate that all preference parameters, including the base rate of time preference, do not differ significantly between the flat and incent groups. However, uncertainty-sensitive types in the flat condition perceive the hazard of not receiving future rewards as much higher than insensitive types. This appears not to be the case for*

[36]Note that the parameter $\gamma$ in the *hyperbolic preference model* and the parameter $\lambda$ in the *hazard rate model* capture a similar property of behavior. It is therefore not possible to estimate a model containing both parameters at the same time.

Table 26: Hazard Rate Model

flat

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.110 | 0.036 | 3.051 | 0.002 |
| $\eta$ | 0.330 | 0.028 | 11.866 | 0.000 |
| $\lambda_0$ | 0.004 | 0.002 | 2.325 | 0.020 |
| $\lambda_U$ | 0.106 | 0.021 | 5.017 | 0.000 |
| $\alpha$ | 0.635 | 0.010 | 62.002 | 0.000 |
| $\beta$ | 0.158 | 0.016 | 10.018 | 0.000 |
| participants | | | | 192 |
| parameters | | | | 8 |
| observations | | | | 8873 |
| $log\mathcal{L}$ | | | | -31276 |

p.e.:parameter estimate, s.e.: standard error.

incent

| | p.e. | s.e. | z | $p$-value |
|---|---|---|---|---|
| $\rho$ | 0.150 | 0.039 | 3.879 | 0.000 |
| $\eta$ | 0.283 | 0.023 | 12.582 | 0.000 |
| $\lambda_0$ | 0.003 | 0.001 | 3.177 | 0.001 |
| $\lambda_U$ | 0.010 | 0.007 | 1.444 | 0.149 |
| $\alpha$ | 0.628 | 0.011 | 54.872 | 0.000 |
| $\beta$ | 0.166 | 0.017 | 9.650 | 0.000 |
| participants | | | | 140 |
| parameters | | | | 8 |
| observations | | | | 6446 |
| $log\mathcal{L}$ | | | | -22332 |

*participants facing real monetary incentives.*

*Support.* Estimation results for the *hazard rate model* are presented in Table 26. The risk preference parameters $\rho$, $\alpha$ and $\beta$ do not differ significantly between the two groups and by and large show similar values as in the *hyperbolic preference model*. What is new, however, is that the *hazard rate model* captures hyperbolic discounting by the hazard probability, transformed by people's probability weights, rather than by hyperbolicity of time preferences themselves. Irrespective of treatment condition, the base hazard rate $\lambda_0$ is estimated to be quite small in both groups, namely between 3 and 4‰. This parameter estimate captures the hazard rate effect for the *insensitive type* ($U = 0$). However, only in the *flat* condition do *sensitive types* ($U = 1$) exhibit a considerably and significantly higher hazard probability of 11% ($\lambda_0 + \lambda_U$). In other words: Participants in this group expect to receive payment only in 89% of all the cases should they actually be entitled to get paid. For the *incent* group, the estimate for $\lambda_U$ is not significantly different from zero but shows the expected sign.

*Discussion.* The estimates of the structural model essentially corroborate our findings from the *hyperbolic preference model* accounting for inherent uncertainty. Because it imposes more structure on the data, the *hazard rate model* yields a somewhat different estimate of the rate of time preference $\eta$ than the corresponding rate $\eta_0$ in the *hyperbolic preference model*.[37] It brings the rate of time preference down to about 28.3% (*incent*) and 33% (*flat*), respectively, but it does not have higher explanatory power than the corresponding hyperbolic preference model.

[37]The respective confidence interval of the *incent* parameter estimate in the *hazard rate model* does not overlap with the *hyperbolic preference model* confidence interval, it only barely overlaps in the *flat* case.

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