Experiments in risk, insurance, and development

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Zusammenfassung

Die drei Artikel dieser Dissertation verwenden experimentelle Methoden, um zu erkunden, wie Individuen Entscheidungen in Gegenwart von Risiko treffen. Die Papiere verbinden Theorie und empirische Evidenz, um Fragen zur intertemporalen Entscheidungsfindung in Gegenwart von Risiko, sowie Versicherungs-entscheidungen in einem Entwicklungsland zu beantworten. Kapitel 1 und 2 konzentrieren sich auf die Weiterentwicklung Theorie und Evidenz fuer grundlegende Entscheidungsmodelle in riskanten und interemporalen Domaenen. Kapitel drei praesentiert ein Feldexperiment, das eingerichtet wurde, um die Substitution zwischen formaler und informeller Versicherung in Accra, Ghana zu untersuchen.

Abstract

The three papers of this dissertation use experimental methods to explore how individuals make decisions in the presence of risk. The papers contribute both theory and empirical evidence to questions about intertemporal decision making in the presence of risk as well as insurance choices in a developing country. Chapters one and two focus on advancing theory and evidence about fundemental decision-making models embedded in risky and intertemporal domains. Chapter three presents a field experiment set up to investigate substitution between formal and informal insurance in Accra, Ghana.

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Preface

This dissertation consists of three papers applying experimental methods to explore how individuals make decisions in the presence of risk. In particular, chapters one and two focus on the nature of intertemporal decision making when risk is mixed in to the decision environment. These two chapters explore fundamental models that govern how economists think about risk, both as a strictly defined mathematical concept, closely approximated by choices over well-defined lotteries in the lab, and as a concept with applications to a vast range of economically significant choices in a variety of contexts such as financial planning, education investments, or insurance.

Chapter three focuses on a particular insurance decision that is highly relevant to risk management in developing countries. We explore how individuals substitute between informal insurance provided via social networks and a formal insurance product provided by the market. In this paper, the focus is not on individual preferences for risk; rather, we examine how beliefs about the effectiveness of insurance affect participation in a particular type of social network. Taken together, the three papers of this dissertation advance insights on risky decision making, identifying how such preferences can be modelled and measured, but also how they interact with social and economic constraints in a variety of contexts across the world.

The papers are thematically linked by the exploration of individual decision-making in the presence of risk. However, they are also methodologically linked by the use of laboratory experiments. Advantages to studying decision behaviour in the lab are listed comprehensively elsewhere in the literature. Lab environments allow for "*ceteris paribus* observations of individual economic agents" [Levitt and List, 2006] allowing researchers to address amongst other things "whether behavior is consistent with the predictions and assumptions of theory and how various mechanisms and institutions affect the behavior of economic agents." [Kessler and Vesterlund, 2015]

The experiments used in the papers of this dissertation each serve a slightly different epistemic purpose. The experiment in chapter one was carefully designed to capture the most salient features of some open puzzles on the interactions between risk and time. With a parsimonious design, we are able to revisit key debates, presenting a rich set of data that answers some questions while highlighting new areas for further study. Most of chapter two is centred around the development and presentation of a new theoretical framework. The associated experiment is designed to highlight

important implications of the theory. Finally, chapter three presents a lab-in-the field experiment where the control that comes from randomised assignment to an economically meaningful treatment allows us to make careful inferences about a complex social interaction that would otherwise be difficult to identify.

Chapter one is based on joint work with Mohammed Abdellaoui, Emmanuel Kemel, and Ferdinand Vieider: "Measuring risk and time preferences in an integrated framework" [Abdellaoui, Kemel, Panin, and Vieider, 2017b]. The paper applies novel extensions of a method familiar to many economists, generating a rich set of data to help organise gaps in the literature on the nature of intertemporal decision making in the presence of risk. We are able to address some open empirical questions: Does hyperbolic discounting persist when both the present and the future are risky? How prevalent is probability weighting as a component of risk attitudes and can it be measured with typical experimental tools? We contribute to an active and lively literature on motivations of non-stationary discounting [Halevy, 2008, Epper, Fehr-Duda, and Bruhin, 2011, Baucells and Heukamp, 2011] by showing that hyperbolic discounting persists even when the present is risky. We also show that probability weighting is an important feature of risk preferences. The importance of these behavioural models of decision-making is strongly demonstrated at the aggregate level. However, our results are also rich enough to point to substantial levels of individual heterogeneity. In short, we provide evidence that contrary to recent theoretical motivations, the riskiness of the future alone cannot explain away hyperbolic discounting. We also show that it is important to account for non-expected utility preferences and that these preferences might have strong implications for discounting. This theme is taken up and explored thoroughly in chapter two.

Chapter two is based on the paper, "Take your chance or take your time" [Abdellaoui, Kemel, Panin, and Vieider, 2017c], written with the same group of coauthors as the work in chapter one. We make three substantive contributions in this paper: We first explore the limitations of current models of intertemporal decision making in the presence of risk. We consider how empirical measures of discounting can be distorted in the presence of risk and how discounted expected utility, the most commonly used model in economics, cannot fully account for these distortions. We then propose a new theoretical framework for thinking about models of intertemporal decision making that can more flexibly account for the presence of risk. In this framework, we relax the assumption that there is a single utility index that captures decision making in risky and riskless situations. We

further allow for risk attitudes that encompass probability weighting and demonstrate how these extensions can affect discount rates. We finally demonstrate the importance of these corrections experimentally.

Chapter three takes risk preferences directly to the field, exploring attitudes towards different sources of insurance in a developing country. Insurance contracts and the beliefs they entail are arguably one of the most important applications of an understanding of risk preferences. This chapter is based on joint work with Emmanuelle Auriol, Julie Lassebie, Eva Raiber and Paul Seabright [Auriol, Lassebie, Panin, Raiber, and Seabright, 2017]. In the paper, we experimentally identify whether individuals substitute between formal and informal insurance. We focus on informal insurance provided by the church, an important social institution that commands a significant financial commitment from participating individuals. The experiment shows that enrollment in a formal insurance policy reduces contributions to the church. We discuss the conditions under which this can be interpreted as evidence for substitution between church and market based insurance.

Taken together, this body of work provides useful insights on risk and time preferences and their applications to policy relevant choices. It also demonstrates a range of experimental methods, carefully highlighting their benefits while being cautious about their limitations for the measurement and estimation of individual preferences.

Chapter 1

Measuring Time and Risk Preferences in an Integrated Framework

1.1 Introduction

Risk and time are fundamentally intertwined—the future is inherently risky. Yet time preferences have mostly been studied abstracting from risk under presumed certainty (see Frederick, Loewenstein, and O'Donoghue, 2002, for a review of the literature). Indeed, it has been posited that deviations from the standard model of inter-temporal decision making, discounted utility with an exponentially decreasing discount function (DU; Samuelson, 1937), may be largely or entirely due to elicitation methods positing certainty of future outcomes [Keren and Roelofsma, 1995, Weber and Chapman, 2005, Halevy, 2008, Gerber and Rohde, 2010, Epper et al., 2011]. According to this intuition, (quasi-) hyperbolic preferences [Phelps and Pollak, 1968, Laibson, 1997, Rohde, 2010, Pan, Webb, and Zank, 2015] are imputable to the absence of risk in the present, while risk is inherent in any future outcomes. A dislike of risk would then result in a choice of immediate outcomes over future ones, regardless of a respondent's true underlying discount rate.

In this paper we present a novel method to elicit time preferences that naturally integrates time and risk. The method consists of a variation on the multiple price lists (MPLs) popularized in economics by Holt and Laury [2002]. We start by using standard MPLs to elicit risk preferences. That is, we compare two non-degenerate binary lotteries while changing the probabilities attached to the different outcomes in a choice list. By eliciting the switching probability between a (relatively) risky and a (relatively) safe lottery, we are able to clearly identify respondents' preferences over risk. In a second step, we elicit time preferences using the same choice setup. The only difference is that the payouts from one of the lotteries are deferred into the future (the resolution of uncertainty is always immediate). By always deferring the outcomes of the *safe* lottery we create a psychological tradeoff between preference for the present and risk aversion, since the price to pay for increased safety is a delay in the payout of the outcome. By administering appropriate delays of both lotteries to different future dates, we can identify quasi-hyperbolic and hyperbolic discounting, going beyond the exponential model.

In addition, we show how to use MPLs to elicit probability weighting jointly with utility curvature. Previous studies were generally not set up to do this (we will return to this point in the discussion). This serves as a stability check of the typical inverse-S shape of probability weighting (see van de Kuilen and Wakker, 2011, for an overview). While different methods have been used to

measure probability weighting (see e.g. Abdellaoui, 2000, and Bleichrodt and Pinto, 2000, for non-parametric measurements), many studies have employed certainty equivalents (*CEs*) to parametrically identify probability weighting functions [Tversky and Kahneman, 1992, Bruhin, Fehr-Duda, and Epper, 2010, Abdellaoui, Baillon, Placido, and Wakker, 2011, L'Haridon and Vieider, 2016]. In these tasks, lotteries with a given probability of winning a prize are compared to a series of sure amounts of money in a choice list. While being eminently tractable, responses in such choice lists may be biased by systematic noise. Recent studies have emphasized how some people may switch systematically towards the middle of a list, or at random [Andersson, Tyran, Wengström, and Holm, 2016, Vieider, 2017]. Using CEs such random choices could result in inverse-S shaped probability weighting even if respondents were in reality expected utility maximizers. The MPLs employed here, however, would result in the opposite pattern based on the random choice explanation, thus providing a stability test for inverse-S shaped weighting functions.

Being able to estimate probability weighting in addition to utility curvature further allows us to examine the effect of the model adopted under risk on the estimated discount function. We start from the estimation of the standard model of inter-temporal decision making in the presence of risk, discounted expected utility (*DEU*), which results from the combination of DU over time with expected utility (*EU*) under risk. We then relax its most restrictive assumptions one by one, by allowing for non-constant discounting and non-linear probability weighting, both of which substantially improve the fit of the model to the data. Accounting for nonlinear probability weighting is also important inasmuch as the curvature of the utility function will influence estimated time discounting, and the latter is generally not the same if estimated under the linear probability assumption of EU or allowing for non-linear probability weighting [Bleichrodt, Abellan-Perpiñan, Pinto-Prades, and Mendez-Martinez, 2007, Schmidt and Zank, 2008].

We find that probability weighting is indeed inverse-S shaped, thus confirming the stylized fact of probabilistic insensitivity and showing the robustness of this finding to the potential confound of random switching. We also reject constant discounting in favor of hyperbolic discounting. Estimating a DEU model with constant discounting and linear probabilities, we estimate a low yearly discount rate of around 6%. Once we allow for nonlinear probability weighting, however, the estimated discount rate more than doubles to 14%. This dramatic change is due to the fact that utility estimated in conjunction with probability weighting exhibits considerably less curvature than util-

ity estimated under the expected utility assumption. This shows that correcting discount rates for utility measures obtained from risky choices under the assumption of expected utility maximization may lead to the systematic underestimation of discounting. We will further discuss these insights after presenting the results.

1.2 Experimental design and model estimation

Subjects. We recruited 100 subjects at the laboratory of the Technical University in Berlin, Germany. The students were from a variety of study majors, 41% were female, and the average age was approximately 22 years. The experiment was computerised and run in 20 small group sessions of five participants each (except for one session with four participants and one with six).

General choice setup. Each MPL presented subjects with two dated lotteries, shown in figure 1.1. The lotteries are constructed in such a way that $x_{r,t} > x_{s,t+\tau} > y_{s,t+\tau} > y_{r,t}$. This means that the lottery to the left of the figure exhibits a higher spread in outcomes than the lottery to the right, so that we refer to it as the *risky* lottery and subscript its outcomes by r. The lottery to the right will be referred to as the *safe* lottery, with its outcomes subscripted by s (neither of these terms were used in the experiment). The subscripts t and $t + \tau$ serve to indicate the date at which the outcomes of the lottery will be paid. In order to elicit risk preferences, we simply set $t = \tau = 0$, so that all payouts take place in the present. We subsequently introduce time delays from the present by introducing $\tau > 0$. We also introduce up-front delays, which will allow us to test for hyperbolic behavior, by introducing $t > 0$. The elicitation task consist in finding the probability for which subjects will switch from a preference for the safe lottery to a preference for the risky lottery. The exact procedures used will be described below.

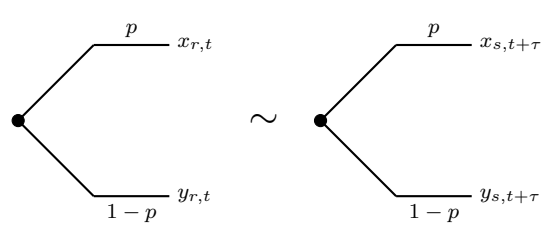


Figure 1.1: General choice setup

Decision model. We next describe our modeling assumptions. We start from a discounted expected utility (DEU) model, where a subject will choose the risky lottery whenever:

$$pD(t)u(x_r) + (1-p)D(t)u(y_r) \geq pD(t+\tau)u(x_s) + (1-p)D(t+\tau)u(y_s), \tag{1.1}$$

where u indicates utility, and $D(t) = e^{-rt}$ the exponential discount function with constant discount rate r. We are furthermore interested in two extensions to this model. One is to replace the linear treatment of probabilities in equation 1.1 by nonlinear probability weighting, thus substituting $w(p)$ for p. The other is to allow for more general functional forms for discounting, $D(t)$, which can capture non-constant discount rates.

Functional forms. For utility, we employ a simple power function, $u(x) = x^{\rho}$. This function is the most commonly used, and we will show below that it provides a good fit for our data. For probability weighting, we use the 2-parameter function proposed by Prelec [1998], $w(p) = \exp(-\gamma(-log(p))^{\alpha})$. The latter fits the data significantly better than 1-parameter functions such as the one proposed by Tversky and Kahneman [1992] ($z = 16.4, p < 0.001$; Vuong, 1989, test), or the 1-parameter version of the same function obtained by imposing $\gamma = 1$ ($\chi^2(1) = 13.23, p < 0.001$; likelihood ratio test). Alternative 2-parameter functions, such as the one proposed by Goldstein and Einhorn [1987], provide a similar fit to the data, and using them instead does not affect our results. The two parameters of the weighting function have a specific interpretation, with α capturing mostly the curvature of the weighting function. Specifically, values of $\alpha < 1$ indicate inverse-S shaped probability weighting, $\alpha = 1$ linearity, and $\alpha > 1$ S-shaped weighting. The parameter γ indicates (mainly) the elevation of the weighting function, with $\gamma > 1$ capturing the typical case of probabilistic pessimism. Finally, we use the so-called $\beta\delta$ function to capture quasi-hyperbolic discounting, resulting in the following functional form for discounting:

$$D(t) = \begin{cases} 1, & \text{if } t = 0 \\ \beta e^{-rt} & \text{otherwise} \end{cases}$$

.

For $\beta = 1$, the function above reduces to the exponential discount function of DEU. Values of $\beta < 1$ capture systematically lower valuations of future outcomes relative to present outcomes. In

addition, we also fit a fully hyperbolic discounting function proposed by Loewenstein and Prelec [1992] to the data. The function takes the form $D(t) = (1+\zeta t)^{\frac{-r}{\zeta}}$, where the ζ parameter captures the degree of deviation from exponential discounting. The limit of this specification as ζ tends to 0 is the exponential discounting function.

Stochastic specification and econometrics. We account for potential noise in the data by incorporating an error term, ϵ_i, into our model. Writing the valuation of the risky lottery as U_r and the corresponding valuation of the safe lottery as U_s, a subject will choose the *risky* lottery if $U_r \geq U_s + \epsilon_i$. We assume ϵ_i to be normally distributed [Hey and Orme, 1994], $\epsilon_i \sim N(0, \sigma_i^2)$. We further allow the error term to depend on characteristics of the specific MPL, indexed by i. In particular, we let the error term depend linearly on the outcome range in the risky prospect, $x_r - y_r$, which provides a good fit to our data (see also Bruhin et al., 2010). The decision problem can then be written as

$$P(\text{choose risky}) = P(\epsilon_i < U_r - U_s) = \Phi\left(\frac{U_r - U_s}{\sigma_i}\right), \tag{1.2}$$

where $P(\text{choose risky})$ indicates the probability of choosing the risky lottery, and Φ is the cumulative normal distribution function. The model can now be estimated by maximum likelihood. To obtain the overall log-likelihood function, we take the natural logarithm of the cumulative distribution function in equation 1.2 and aggregate it over prospects and decision makers as follows:

$$LL(\boldsymbol{\theta}) = \sum_{n=1}^{N}\sum_{i=1}^{43} \ln\left(\mathbb{1}_{\mathbb{r}}\Phi\left(\frac{U_r - U_s}{\sigma_i}\right) + (1-\mathbb{1}_{\mathbb{r}})[1-\Phi\left(\frac{U_r - U_s}{\sigma_i}\right)]\right) \tag{1.3}$$

where $\mathbb{1}_{\mathbb{r}}$ is an indicator variable that is equal to 1 if the risky prospect is chosen, and equal to 0 if the safe prospect is chosen, and $\boldsymbol{\theta}$ is the parameter vector to be estimated such as to maximize the log-likelihood function. The likelihood model is estimated using the Broyden-Fletcher-Goldfarb-Shanno optimization algorithm and errors are clustered at the subject level.

Identification of risk preferences. We identify risk preferences from choices amongst lotteries with payouts in the present ($t = \tau = 0$). Table 1.1 shows a list of the MPLs used for the elicitation. MPLs 1 to 5 in the list keep the expected value switching probability (i.e., the probability at which an expected value maximiser would switch from the safe lottery to the risky one) fixed

at 0.44—the switching probability originally used by Holt and Laury [2002]. These MPLs were constructed to systematically differ in terms of outcomes, allowing us to scan the outcome range and to thus identify utility curvature. On the other hand, we constructed prospect pairs 6 to 12 explicitly in such a way as to scan the probability interval in terms of expected value (EV) switching probabilities.[1] While other studies have tried to estimate probability weighting using MPLs, they usually presented too narrow a range of EV switching points to be able to cleanly separate utility curvature from probability weighting. For instance, Andersen, Harrison, Lau, and Rutström [2014] used four MPLs with a range between 0.30 and 0.45, finding S-shaped probability weighting. The power to clearly identify probability weighting is likely to be lacking in their design, since it is well known that probability weighting functions tend to be relatively flat and close to linearity for the types of ranges of EV switching points used. This issue may be further confounded by noise in the data. By systematically introducing variation in EV switching probabilities, we solve this issue and augment the power to separately identify probability weighting and utility curvature.

Table 1.1: Prospect pairs to identify risk preferences

MPL nr.	outcomes in €	EV prob.
1	(250, 10) vs. (200, 50)	0.44
2	(300, 20) vs. (200, 100)	0.44
3	(500, 0) vs. (250, 200)	0.44
4	(500, 20) vs. (400, 100)	0.44
5	(500, 220) vs. (400, 300)	0.44
6	(500, 10) vs. (150 , 50)	0.10
7	(500, 220) vs. (300, 250)	0.13
8	(450, 150) vs. (250, 200)	0.20
9	(500, 10) vs. (450, 50)	0.44
10	(350, 50) vs. (250, 200)	0.60
11	(500, 0) vs. (350, 300)	0.67
12	(500, 0) vs. (400, 350)	0.78

Before moving on to time preferences, we quickly discuss the issue of random switching. Assume that some subjects switch at random points in a list (a tendency to switch towards the middle of a list results in the same prediction). On average, such subjects will exhibit a switching probability of 0.5. Now take MPL 6. Since a risk neutral respondent would switch to the risky lottery at $p = 0.1$, a risk seeker would switch to that lottery at an even lower probability. Since the choice

[1] This is done by systematically adjusting the outcome spread in the two prospects. Let $k = \frac{x_r - x_s}{y_s - y_r}$. Then we can solve the expected value of the choice probelm for $p(EV) = \frac{1}{1+k}$. It is now straightforward to manipulate k in such a way as to obtain EV switching probabilities $p(EV)$ that scan the probability interval.

list ranges over the whole probability interval, however, random switching behavior would result in an estimate of risk *averse* behavior. Conversely, for MPL 12, a risk averse subject would switch to the risky lottery only once the probability is above 0.78. That is, random choices would be counted towards risk *seeking*. We conclude from this that systematic noise in the form of random switching would result in an S-shaped probability weighting function in the current setup. This is exactly the opposite of what happens for CEs, where random choice is potentially confounded with inverse-S probability weighting, thus constituting an test for the importance of systematic noise in the identification of probability weighting.

Identification of time preferences. Time preferences are identified by delaying the payouts of the lotteries into the future (the uncertainty is always resolved immediately after the experiment). Table 1.2 provides an overview of the choice tasks used to identify time preferences. The EV switching probability is now always fixed at 0.44. All the different MPLs are repeated for all time delays, which are fixed at $(t, t+\tau) = \{(0,3); (0,6); (0,9); (0,12); (6,12); (9,12)\}$ months. By comparing the lottery choice resulting from $t = 0, \tau > 0$ to the equivalent choice for $t = 0, \tau = 0$, we obtain an estimate of discounting. By further comparing choices in MPLs with constant delays, $(0, \tau)$ and $(t, t+\tau)$, we can determine whether the discount rate is constant, or whether discounting follows a hyperbolic pattern.

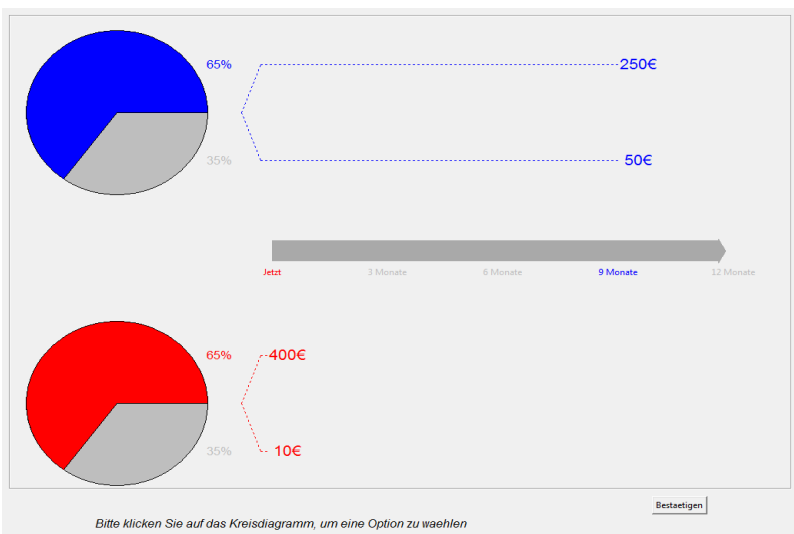
Table 1.2: Prospect pairs to identify time preferences

MPL nr.	outcomes in €	EV prob.
1	$(250_t,\ 10_t)$ vs. $(200_t+\tau,\ 50_t+\tau)$	0.44
2	$(300_t,\ 20_t)$ vs. $(200_t+\tau,\ 100_t+\tau)$	0.44
3	$(500_t,\ 0_t)$ vs. $(250_t+\tau,\ 200_t+\tau)$	0.44
4	$(500_t,\ 20_t)$ vs. $(400_t+\tau,\ 100_t+\tau)$	0.44
5	$(500_t,\ 220_t)$ vs. $(400_t+\tau,\ 300_t+\tau)$	0.44

Choice procedures. The experiment consisted of 42 distinct choice lists. Three of these lists were randomly selected for each subject and repeated during the experiment, so that subjects completed a total of 45 choice lists. The order of questions was randomised at the subject level. Within each choice list, the amounts were kept fixed but the probabilities varied across each row in steps of 5%. In order to focus subjects' attention, choices were presented one by one. A screenshot of a choice problem is shown in figure 1.2. The figure shows a choice between a risky lottery, offering either

€400 with a probability of 0.65 or else €10, both to be paid now, against a safe lottery offering the same probability of €250 or else €50 in 9 months. The probability of winning was adjusted according to the choice using a bisection mechanism. It was, however, made clear to subjects that this mechanism served purely as a decision aid to quickly fill in the choice list. Once all the choices for a given list had been taken and the list was thus fully filled in, subjects were shown the complete choice list and explicitly encouraged to amend their choice in case they were not happy with it. Importantly, it was made clear to them that the full list would be used for the final extraction of the payout-relevant choice, with all probabilities equally likely to be selected.

Figure 1.2: Screenshot from time preference section of experiment



Incentives and randomisation. Subjects were paid a fixed amount of €15 for their participation. In addition, we used a random incentive mechanism whereby each subject had a 1 in 10 chance of receiving payment for their choices. This allowed us to use high monetary stakes ranging up to €500, which are important when estimating utility functions, as well as for the estimation of time discounting. Subjects were informed that if they were selected to play the tasks for real money, one of the choice lists would be selected at random. Within that choice list, one probability would then be selected, and the lottery of their choice would be played out for that probability.

Delayed payouts. The participation fee of €15 was paid directly after the experiment was over. All other payouts were made by bank transfer initiated at time t or $t + \tau$. This meant a fixed

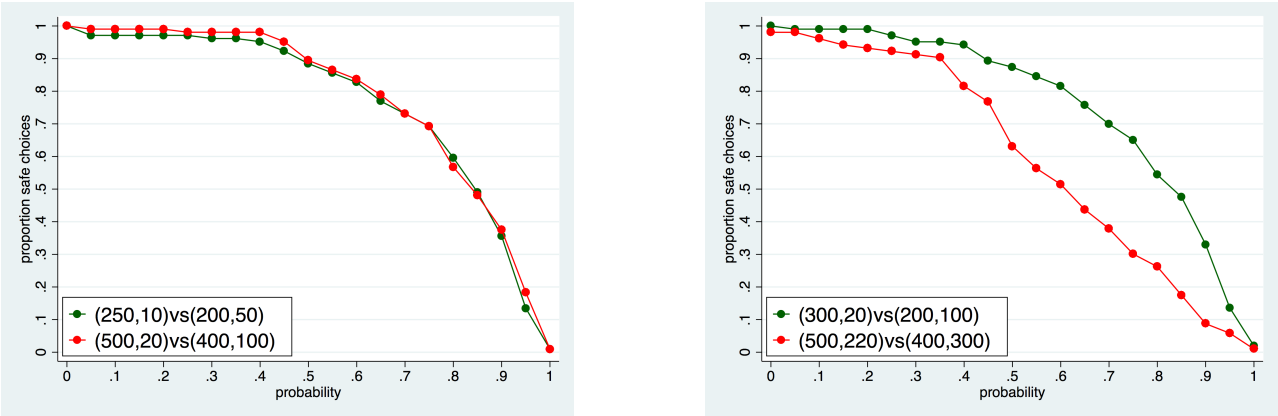
upfront delay of 3 days between the date indexed by t and the day the subject would have the money available for consumption, which for consistency was also kept for later dates. This serves to address worries that any present bias observed may be driven by the immediacy of the current payoff [Coller and Williams, 1999]. All payments were guaranteed by the WZB Berlin Social Science Center, which was familiar to participants inasmuch as it is one of the institutions running the lab. Subjects were given a certificate indicating the amount won and the day on which the transfer would take place, which was signed by the experimenter. The certificate also contained the address, email address, and phone number of the person responsible of the payouts at the WZB. Subjects were explicitly encouraged to get in touch in case their bank details changed, or if they had any doubt about the payout procedure.

1.3 Results

1.3.1 Non-parametric results

We begin our analysis by presenting some nonparametric results that convey a feeling for our main findings. Figure 1.3 shows two plots, which together constitute a test of whether utility follows constant relative risk aversion (*CRRA*, i.e. a power function) or constant absolute risk aversion (*CARA*; i.e. an exponential function). If utility exhibits CRRA, the choice patterns for the two MPLs shown in panel 1.3a, (500, 20) vs. (400, 100) and (250, 10) vs. (200, 50), ought to be identical. This is because the former MPL can be obtained from the latter by doubling all outcomes, so that the relative risk remains constant across MPLs. A similar test is shown for CARA in panel 1.3b. Here one of the MPLs, (500, 220) vs. (400, 300), is obtained from the other, (300, 20) vs (200, 100), by adding a fixed amount of €200 to each outcome. Choice behavior ought to be the same in the two MPLs if subjects exhibit CARA utility due to the exponential form of the utility function. The distributions of choices in the CRRA comparison coincide almost perfectly ($z = 0.293, p = 0.770$, Mann-Whitney test on switching probabilities). In the CARA comparison, on the other hand, the proportion of safe choices is always lower and drops off more sharply for the second MPL ($z = 4.78, p < 0.001$).

We next examine choice behavior in the MPLs scanning the probability interval. Figure 1.4 plots choices for lotteries pairs 6 to 12 from table 1.1. We would expect the proportion of safe



(a) CRRA test

(b) CARA test

Figure 1.3: Nonparametric test of CRRA and CARA utility

choices to drop off more quickly for MPLs with a lower expected value switching point. This is indeed mostly the case. More interestingly, we can use the choices to garner a first impression of whether risk preferences may change with the level of the EV switching point. For example, for the prospect pair (500 , 220) vs. (300 , 250), with an EV switching probability of $p = 0.13$, the proportion of safe choices drops quickly and by the EV probability, about 50% of participants have stopped choosing the safe option. This is an indication of risk neutral behavior. At the other extreme of the probability interval, for the prospect pair (500, 0) vs. (400, 350) with an EV switching probability of $p = 0.78$, close to 90% of subjects are still choosing the safe prospect by the EV probability—an indication of considerable risk aversion for large probabilities. At the same time, however, we also observe considerable heterogeneity in choice behavior between MPLs with relatively similar EV switching probabilities. This points at the importance of utility curvature in addition to probability weighting.

This leaves the effect of time delays to be discussed. Figure 1.6 focuses on one specific MPL, (500, 220) vs. (400, 300), and presents distributions of choices for this pair at the 5 different time delays from $t = 0$ (results for other MPLs are similar). The proportion of safe choices at different probabilities is highest in the present by some distance. As choices are delayed into the future, subjects choose the risky, sooner option more frequently, just as one would expect. For the longest delay of $\tau = 12$ months, 60% of subjects prefer to choose the risky, sooner lottery even when there is a 0% probability of obtaining the high outcome. This indicates a preference for €220 now over €300 in 12 months' time, thus implying a yearly discount rate of 36% or greater under a linear

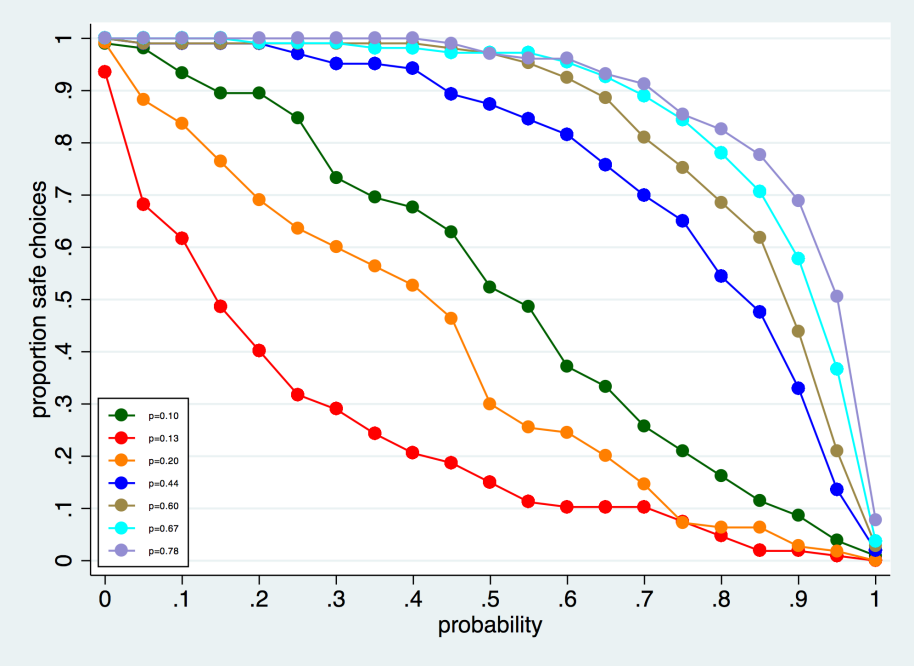


Figure 1.4: Choicelists in the present spanning a range of expected value switching points

utility assumption (which we will abandon in due time).

Finally, we take a look at whether discount rates are constant or whether there is an indication of (quasi-) hyperbolic behavior in our data. Figure 1.6 shows comparisons between choices in pairs of MPLs that can be used to identify such behavior. Panel 1.6a shows choices for the MPLs with a 3 months delay from the present versus a three months delay from 9 months, while panel 1.6b shows choices for the MPL with a 6 months delay from the present versus the MPL with a 6 months delay from 6 months. Under constant discount rates, we would expect these two pairs to show identical choice patterns. Present bias, on the other hand, would make the risky lottery more attractive when there is no upfront delay (i.e., when $t = 0$). This is indeed what we observe, providing a first indication of present bias in our data.

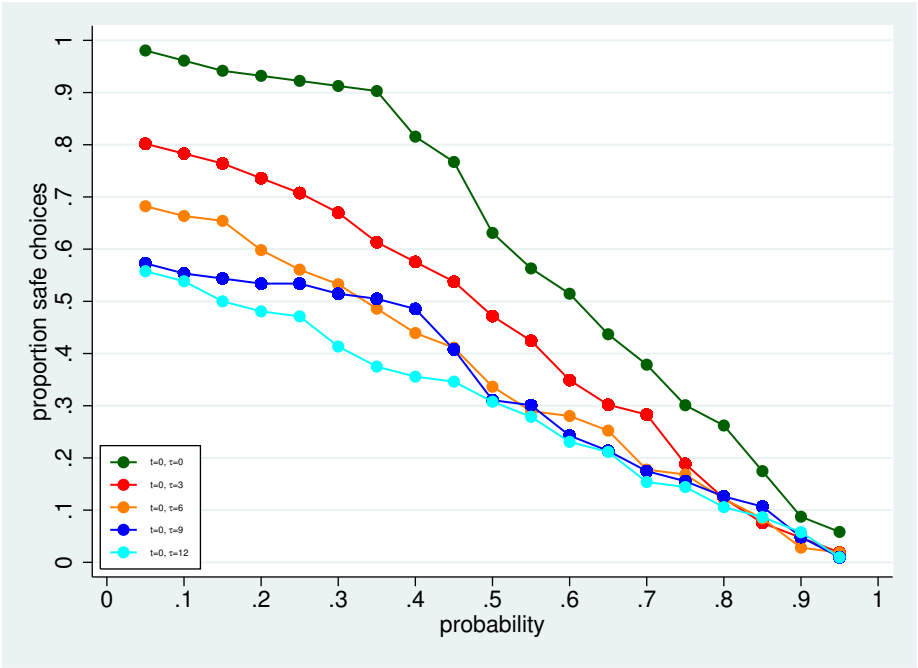
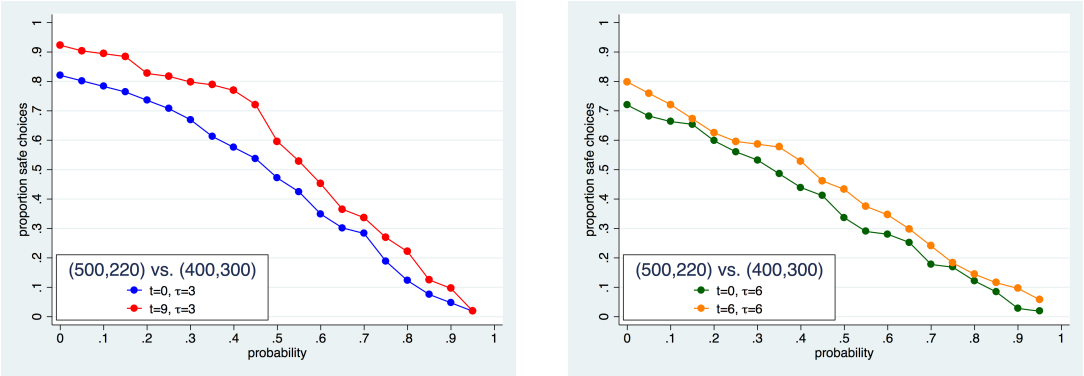


Figure 1.5: Choices for MPL (500, 220) vs (400, 300) with different delays from $t = 0$



(a) Choice patterns for 3 months delays **(b)** Choice patterns for 6 months delays

Figure 1.6: Nonparametic test of (quasi-) hyperbolic behavior

1.3.2 Parametric estimations

Table 1.3 presents the results of our structural estimations. Column 1 presents the DEU model, assuming linear probabilities and constant discounting. We find a considerable degree of utility curvature, while the yearly discount rate is estimated to be quite low at 5.9%.

The second column reports parameters for what we call the discounted rank-dependent utility model ($DRDU$). This model combines constant discounting with a model under risk allowing

for both utility curvature and nonlinear weighting of probabilities. The functional fit is improved considerably relative to the DEU model ($\chi^2(2) = 4094.83, p < 0.001$; likelihood ratio test). The sensitivity parameter α is clearly smaller than 1, indicating an inverse-S shaped probability weighting function. This shows that the estimation of such functions is robust to using a method in which systematic noise would work against inverse-S weighting. We also find a considerable degree of probabilistic pessimism, captured by $\gamma > 1$.

Table 1.3: Parameter estimates of structural models

parameter	DEU	DRDU	QHRDU	HRDU
ρ (utility curvature)	0.273	0.512	0.517	0.514
95% CI	(0.268, 0.279)	(0.499, 0.526)	(0.503, 0.531)	(0.5, 0.528)
r (discount rate)	0.059	0.141	0.111	0.239
95% CI	(0.056, 0.061)	(0.135, 0.148)	(0.103, 0.119)	(0.211, 0.268)
α (prob. sensitivity)		0.675	0.672	0.674
95% CI		(0.655, 0.694)	(0.652, 0.691)	(0.654, 0.693)
γ (prob. pessimism)		1.405	1.42	1.411
		(1.364, 1.447)	(1.378, 1.462)	(1.369, 1.452)
β (<1: present bias)			0.972	
			(0.967, 0.977)	
ζ (hyperbolicity)				1.788
				(1.201, 2.376)
σ (noise)	0.002	0.008	0.008	0.008
	(0.002, 0.002)	(0.007, 0.009)	(0.007, 0.009)	(0.007, 0.009)
max LL	-37348.93	-36130.75	-36073.05	-36066.97

Figure 1.7 depicts the probability weighting function estimated in the DRDU model (functions estimated in other models allowing for probability weighting are very similar). The function clearly exhibits an inverse-S shaped pattern, confirming previous results [Tversky and Kahneman, 1992, Wu and Gonzalez, 1996, Abdellaoui, 2000]. At the same time, the inflection point falls relatively low, and the degree of probabilistic pessimism is quite high. This may be due to one of two possible factors. One, we used real incentives up to €500, which are higher than in most experiments. To the degree that relative risk aversion increases with stakes, this may be reflected in a lower probability weighting function [Fehr-Duda, Bruhin, Epper, and Schubert, 2010, Bouchouicha and Vieider, 2017]. Two, the type of MPL task used may result in systematically higher estimates of risk aversion than alternative measurement techniques. Given the setup of the MPLs, there is less space in most lists to detect risk seeking than risk aversion. This design element may well influence the

overall estimate of risk aversion, although comparative data would be needed to clearly establish this.

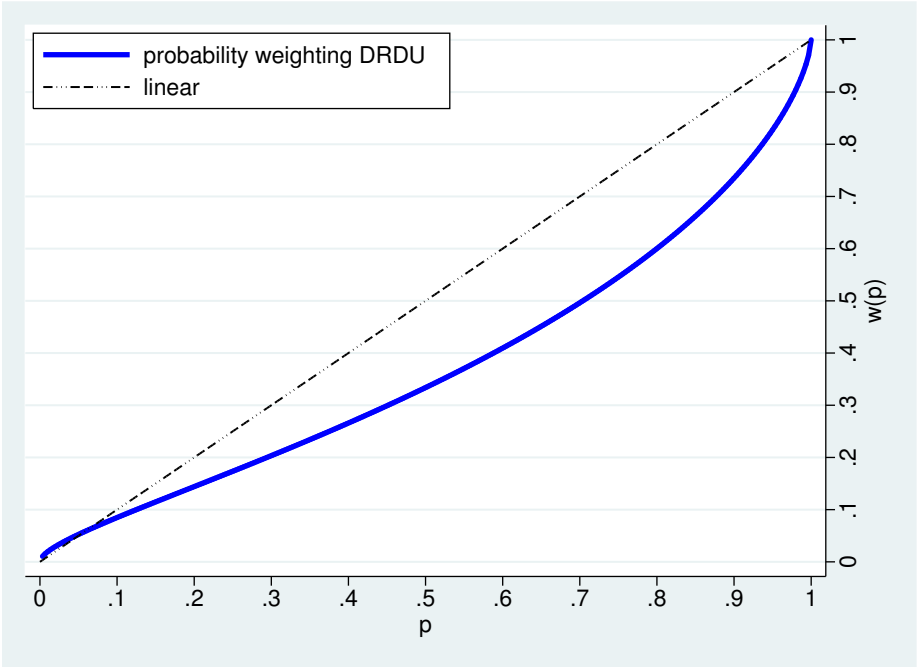


Figure 1.7: Probability weighting function estimated in RDRU model

The corollary of the high level of pessimism we find is a utility function that exhibits significantly less curvature in the DRDU model than the one estimated under DEU. This, in turn, also impacts the estimate of the discount rate, which at over 14% is now more than twice as high as the one estimated under DEU.

The model in column 3 relaxes the assumption of constant discounting, and instead allows discounting to be quasi-hyperbolic. This further increases model fit ($\chi^2(1) = 112.02, p < 0.001$; likelihood ratio test). The β parameter is significantly smaller than 1, indicating present bias. Finally, column 4 presents an RDU model combined with a fully flexible hyperbolic discount function. Compared to the RDU model with quasi-hyperbolic discounting, this model fits the data even better ($z = 1.90, p = 0.02$; Vuong test), providing some evidence for fully hyperbolic behavior.

1.3.3 Individual estimates

The results discussed up to this point are derived from aggregate estimates of the choice data. It is, however, well-known that there is considerable heterogeneity in individual preferences. Table 1.4

presents summary statistics of these estimates for our two best-fitting models, QHRDU and HRDU. The individual estimates of these models converged for 87 and 83 of our 100 subjects respectively. In addition to descriptive statistics of the distribution of estimates, the table reports the number of statistically significant parameter estimates. The significance is measured against appropriate benchmarks for the different parameters, i.e. against 1 for utility curvature, probabilistic sensitivity, probabilistic pessimism, and the present-bias parameter in the QHRDU model; and against 0 for the discount rate, noise, and the hyperbolicity parameter.

Table 1.4: Individual-level estimates of QHRDU and HRDU models

QHRDU model					
Parameter	1stQ	Median	3rdQ	Mean	Nr. significant
ρ (utility curvature)	0.27	0.45	0.61	0.45	83
α (prob. sensitivity)	0.51	0.76	1.13	0.82	54
γ (prob. pessimism))	1.01	1.31	1.79	1.52	59
r (discount rate)	0.05	0.12	0.23	0.16	67
β (<1: present bias)	0.96	0.99	1.01	0.98	42
σ (noise)	0.00	0.00	0.01	0.01	68

Based on N=87 subjects; the model did not converge for 13 subjects.

HRDU model					
Parameter	1stQ	Median	3rdQ	Mean	Nr. significant
ρ (utility curvature)	0.26	0.44	0.61	0.44	76
r (discount rate)	0.04	0.15	0.41	0.34	52
α (prob. sensitivity)	0.52	0.74	1.15	0.82	53
γ (prob. pessimism)	1.01	1.35	2.02	1.65	58
ζ (hyperbolicity)	0.73	2.24	4.17	4.26	33
σ (noise)	0.00	0.00	0.01	0.01	61

Based on N=83 subjects; the model did not converge for 17 subjects.

Some interesting features stand out. We found strong probabilistic insensitivity in the aggregate estimates, and 62% of subjects exhibit statistically significant probabilistic insensitivity. At the same time, close to 70% of subjects exhibit a pessimism parameter significantly different from 1. Overall, for 15% of subjects both sensitivity and pessimism were not significantly different from 1. This gives a rough estimate of the number of subjects for whom we cannot reject the expected utility decision model. The number of subjects following expected utility in our setup is indeed quite similar to the proportion of EU followers estimated by Bruhin et al. [2010] employing a finite mixture model. In terms of time preferences, we find that we can reject the null of non-hyperbolic

preferences for approximately 50% of subjects according to the quasi-hyperbolic model and 40% of subjects under the fully-hyperbolic model.

1.4 Discussion and conclusion

In this paper, we presented results from a comprehensive multiple price list experiment to elicit risk and time preferences in an integrated framework. Using a variation on a popular multiple price list design, we were able to estimate time preferences in addition to risk preferences. We did so in a context of pervasive risk, which may be more realistic than the artificial certainty assumed by the majority of elicitation designs to date. In addition, we designed the choice lists with the explicit goal to allow us to separate utility curvature from probability weighting. Introducing orthogonality between stakes and probabilities, and scanning the probability interval, we were able to show that typical patterns of inverse-S shaped probability weighting are stable to the use of this method.

In the context of time preferences, we found clear evidence for present bias and hyperbolic behavior. This evidence is contrary to some previous studies that had shown present bias to disappear once risk was added to the elicitation mechanism [Keren and Roelofsma, 1995, Weber and Chapman, 2005]. In terms of discount rates, we found the estimated yearly rate to be as low as 6% when adopting discounted expected utility. Adopting a rank-dependent formulation including probability weighting instead, however, more than doubled the estimated discount rate to 14%. This shows that using utility curvature obtained from risky decisions and estimated under the assumption of expected utility theory, as proposed by Andersen, Harrison, Lau, and Rutström [2008], is problematic, and may lead to artificially low estimates of discounting. More generally, it points towards the importance of a careful treatment of utility in the assessment of discounting.

Finally, we showed that inverse-S shaped probability weighting is stable to the use of the particular form of multiple price list we used. This is important, inasmuch as systematic noise under the form of random switching (or switching towards the middle of a list) could potentially distort estimates of probability weighting. In the particular design used, however, this bias would work *against* inverse-S shaped probability weighting. The fact that we replicated the typical inverse-S shape thus shows the stability of the empirical phenomenon.

Some studies have reported different shapes of probability weighting, including the opposite pattern of S-shaped probability weighting. For instance, Harrison, Humphrey, and Verschoor [2010]

reported S-shaped probability weighting from four developing countries. Andersen et al. [2014] and Andersen, Harrison, Lau, and Rutström [2017] reported S-shaped probability weighting estimated based on the same type of choice lists as used in this paper. The latter finding is likely due to poor discriminatory power between utility curvature and probability weighting, given a narrow range of expected value switching probabilities in the stimuli, and potentially to the presence of noise. The findings in the former study are likely to be driven by the restrictive assumption of a 1-parameter probability weighting function. Indeed, L'Haridon and Vieider [2016] showed that probabilistic sensitivity is one of the few universal behavioral patterns in student populations from 30 countries. Vieider, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson, and Mekonnen [2016] generalized this finding to a representative rural population sample from Ethiopia. We thus conclude that – notwithstanding some claims to the contrary – inverse-S shaped probability weighting is alive and in good health.

Chapter 2

Take Your Chance or Take Your Time. On the Impact of Risk on Time Discounting

2.1 Introduction

Discounted Expected Utility (DEU) – the workhorse of modern economics when it comes to the modeling of savings and consumption in the presence of risk [Becker and Mulligan, 1997, Yaari, 1965, Zeldes, 1989] – results from the combination of two separate lines of inquiry regarding individual decision making. The first suggests to evaluate deterministic streams of outcomes by a sum of utilities of outcomes weighted by exponentially decreasing discount factors, hence resulting in the discounted utility model (DU; Samuelson, 1937). The second line of inquiry focuses on atemporal decision making under uncertainty and has resulted in the popular expected utility model (EU, Savage, 1954, von Neumann and Morgenstern, 1944). Under DEU, a risky prospect over deterministic streams of outcomes is evaluated as the expectation of the discounted utilities of those streams. Whether a choice involves risky intertemporal tradeoffs or not, DEU uses one and the same discount function and utility index to evaluate objects of choice.[1]

The validity of assuming identical utility functions for risk and time has been questioned by recent empirical investigations [Abdellaoui, Bleichrodt, L'Haridon, and Paraschiv, 2013, Andreoni and Sprenger, 2012, Brown and Kim, 2014]. This creates at least two potential problems that

[1] Formally, in the present paper we opt for a simplified version of DEU where outcomes are directly assigned an objective probability instead of probabilities resulting from an explicitly given history of events. In our setup no delayed resolution of uncertainty occurs, which is in contrast to Kreps and Porteus' [1978] recursive expected utility.

could bias measurements of intertemporal choice parameters. First, the very presence of risk may impact the measurement of utility and discounting. For instance, Anderhub, Güth, Gneezy, and Sonsino [2001] report experimental findings showing that less risk tolerant agents discount the future more heavily. Similarly, Dean and Ortoleva (2016, Section 3.3) report a significant correlation between risk aversion and the discount rate, as well as a strong correlation between risk aversion and present bias. Second, widely documented deviations from the standard theories, such as non-linear probability weighting under risk [Barseghyan, Molinari, O'Donoghue, and Teitelbaum, 2013, Bruhin et al., 2010, Wakker, 2010] and non-exponential discounting over time [DellaVigna and Malmendier, 2004, Laibson, 1997, Rohde, 2010], may further impact the relevant parameters.

The present paper introduces a generalization of DEU that accommodates these potential problems by incorporating three descriptively desirables features. The first consists in allowing for differences of the utility for time and the utility for risk, i.e. a *domain-specific* utility index. This feature builds on an extension of DEU investigated in Abdellaoui et al. [2017b] and Miao and Zhong [2015]. As we will show shortly, the formalization of this generalization implies that risk will not only impact utility, but also discounting. The second feature is that the new preference functional encompasses a parameter-free discount function, hence allowing for discounting patterns other than exponential discounting, such as quasi-hyperbolic or hyperbolic discounting [Loewenstein and Prelec, 1992, Olea and Strzalecki, 2014, Phelps and Pollak, 1968]. The third characteristic consists in allowing for non-linear probability weighting under risk, capturing the common ratio and certainty effects [Allais, 1953]. This again has implications for both utility and discounting. This last feature indirectly builds on recent contributions on the impact of probability weighting on discounting [Epper et al., 2011, Epper and Fehr-Duda, 2014, Halevy, 2008, Saito, 2015]. Combining recent modeling approaches based on domain-specific utilities and probability weighting into one unified theoretical framework enables us to organize a variety of recent empirical findings that would be considered puzzling under DEU, or even under some extensions of that model (which constitute restrictions of our model).

In the present paper, we show that a "risk-time" setup, where objects of choice are probability distributions over streams of deterministic outcomes, allows for a natural bridging of time discounting and the modeling of inherent uncertainty about the future (Section 2.1). To bridge the time and risk domains in our setup, we propose *the risk equivalent method*, an elicitation tool that represents

temporal discounting with respect to a given outcome as a *subjective probability* to immediately obtain that same outcome. For instance, an agent could be indifferent between obtaining \$200 in six months' time, represented as (x, t), and a prospect that gives her the same \$200 immediately with an 80% probability, represented as (x, p).[2] Under DEU, this indifference implies that the value of the temporal prospect, $D(t)u(x)$, where D and u stand for the discount and utility function respectively, will be equal to the value of the risky prospect, $pu(x)$. Because DEU uses a single utility index for both time and risk, we can cancel out the term $u(x)$ and obtain

$$D(t) = p. \tag{2.1}$$

This means that one can fix a time t along with an outcome x and directly obtain the corresponding discount factor from the matching probability p.[3] In terms of the previous example, the agent applies a discount factor of $D(t) = 0.8$ when the receipt of \$200 is delayed by six months. By construction, such a (matching) probability accounts for the agent's belief that the promised future outcome may vanish. This approach mimics that of Anscombe and Aumann's [1963] subjective EU.[4]

Notice how this setup allows us to nonparametrically measure discounting under DEU without having to worry about measuring utility. Traditional measurements of discounting have often assumed linear utility, which may bias the elicited function if utility is truly nonlinear (Frederick et al., 2002, p. 381). Our method allows us to access the discount function directly and without the utility confound when assuming DEU.[5] It furthermore can also be used to illustrate in an intuitive fashion the potential biases in estimated discounting that could result from domain-specific utility functions for risk and time, and from non-linear probability weighting.

Recently reported violations of DEU suggesting the existence of specific utility indices for risk

[2]Within our "time-risk" setup, (x, t) can be identified with the lottery giving (x, t) with certainty. Similarly, lottery (x, p) consists of the lottery giving x at $t = 0$ and nothing otherwise.

[3]Takeuchi (2011) uses a two step procedure to elicit discounting that results in Eq. (1). His method consists in separately assuming DU for temporal prospects and EU for risky prospects. A single utility index is used for risk and time. Then, he fixes two outcomes x and y, $x > y$, and finds the probability p such that the agent is indifferent between (x, p) and $(y, 1)$, which implies $p = u(y)/u(x)$ under EU. In a second step, he elicits the delay t such that the agent is indifferent between (x, t) and $(y, 0)$, which implies $D(t) = u(y)/u(x)$ under DU. Putting the two steps together, he obtained the equation $D(t) = p$.

[4]In particular, the availability of objective probabilities makes it possible to assign subjective probabilities to uncertain events through matching probabilities. The subjective probability of an uncertain event E is thus determined by finding the matching probability p that makes the agent indifferent between (x, p) and the gamble that gives x when E occurs and nothing otherwise, i.e. (x, E). This allowed Anscombe and Aumann [1963] to bridge risk and uncertainty under EU.

[5]Another method to elicit discounting without the interference of utility was recently proposed by Attema, Bleichrodt, Gao, Huang, and Wakker [2016] within a DU framework.

and for time indeed cast doubt on the capacity of Eq. (2.1) to elicit discounting in an unbiased fashion (e.g., Brown and Kim 2014, Miao and Zhong 2015). In particular, they show that, contrary to the assumption underlying DEU, intertemporal utility differs from risky utility. Assume now a specific utility scale, v, for intertemporal tradeoffs between deterministic outcomes, and a different utility scale, u, for risky tradeoffs. Having two utility scales over the same set of outcomes means that there necessarily exists a strictly increasing function ϕ that transforms the intertemporal utility scale v into the risky utility scale u, i.e. $u = \phi \circ v$. Since the value of (x, t) is measured on the scale v, one needs to convert it into the scale u when evaluating the aforementioned indifference between (x, t) and (x, p), which involves both time delays and risk. The new equation thus becomes $\phi[D(t)v(x)] = pu(x)$. After normalizing both utility scales[6], we obtain

$$D(t) = \phi^{-1}(p), \tag{2.2}$$

where ϕ^{-1} stands for the inverse of ϕ. This shows that the assumption of domain-specific utility functions necessarily impacts discounting as well. In other words, one would expect that discounting elicited in risky environments is not the same as discounting obtained from riskless tradeoffs if the utilities for time and risk are indeed different.

Even once one allows for different utility under risk and over time, another potential source of bias in the measurement of discounting results from the long list of observations showing that most people transform probabilities in a non-linear fashion [Barseghyan et al., 2013, Bruhin et al., 2010, Tversky and Kahneman, 1992]. Allowing for a probability weighting function, w, that transforms probabilities into decision weights, Eq. (2.2) becomes

$$D(t) = \phi^{-1}[w(p)]. \tag{2.3}$$

This equation shows how nonlinear probability weighting may impact discounting when risk and time are simultaneously at play (see also Epper and Fehr-Duda, 2015).[7] More specifically, the use of

[6] Because u and v are unique only up to a positive linear transformation, one can use the normalization conditions $u(x) = v(x) = 1$ for a fixed outcome x.

[7] Baucells and Heukamp [2011] propose a "time-risk" model restricted to the evaluation of prospects (x, p, t) with a domain-independent utility function and a "probability weighting-like" function. In fact, such probability weighting is intrinsically related to probability discounting over time (resulting from tradeoffs between p and t), and not to nonlinearity of utility in the probabilities under risk (resulting from tradeoffs between p and x). Thus, when comparing prospects (x, t) with prospects (x, p) as we propose, the predictions of their model coincide with DEU with a constant discounting function. In other words, for comparisons as used in this paper, and in contrast to Eq. (3), Baucells

the risk equivalent method in a setting where agents assign domain-dependent utilities to outcomes and transform probabilities nonlinearly results in discount factors that are impacted by both ϕ and w. Eq. (2.3) then points to a generalization of DEU that combines a domain-dependent utility specification with rank-dependent utility for risk.

Equation (2.3), resulting from our generalized DEU model (henceforth *GDEU*), combines into one single model two different extensions of DEU investigated in Miao and Zhong [2015]. The first assumed DEU with domain-specific utility functions. The second extension assumed non-linear probability weighting while using a single utility index for both risk and time. In our integrated theoretical framework, estimating the components u, v, and w while allowing for fully general discount functions, we provide a precise assessment of the impact of imposing one single utility function for time and risk and linear probability weighting on the elicitation of discounting. The descriptive power of our general model can thus be evaluated simply by checking whether allowing for domain-specific utilities along with nonlinear probability weighting as suggested by our GDEU model results in a convergence between the discount function obtained from DU in a riskless environment and that obtained from risk equivalents. We can also investigate whether any one of the previously discussed extensions of DEU by itself is sufficient to obtain an unbiased discount function, and thus to identify the most parsimonious model allowing for the unbiased measurement of discounting.

To test our model, we experimentally measure discounting under risk and in riskless environments. We find discount factors to differ significantly between the two setups and to do so systematically, with more pronounced discounting in riskless environments than under risk. This points to the importance of risk for the measurement of time discounting, as predicted by our model. We find risky utility to be more concave than inter-temporal utility, confirming previous findings and showing the importance of modeling this difference explicitly. We then proceed to correcting the discount factors obtained under risk by adjusting them for the difference in utilities ϕ and for probability weighting w, as postulated in our model. The correction closes the gap between the risky and riskless discount factors, thus empirically validating our modeling approach. We also show that the correction for different utility curvatures in itself is not sufficient to obtain this result, although it somewhat narrows the gap between the two discount functions. Finally, we show that exponential discounting is violated in our data both under risk and in riskless environments.

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et al. 's (2012) model cannot account for the potential impact of probability weighting on discounting in decisions under risk (see also Abdellaoui, Baucells, Cappelli, and Kemel, 2017a).

The present paper proceeds as follows. Section 2.2 introduces the theory and measurement approach. Section 2.3 presents the results in four subsections: 2.3.1 presents nonparametric results derived directly from risk equivalents based on DEU; 2.3.2 compares discount factors obtained from risk equivalents under DEU to discount factors measured in a riskless environment (DU); 2.3.3 compares risky and riskless utility; 2.3.4 applies correction factors derived from our model to discounting under risk and compares the corrected discount factors thus obtained to the riskless discount factors; and section 2.3.5 discusses discounting patterns. Finally, section 2.4 discusses the results and concludes the paper.

2.2 Theory and measurement

The present section is divided into four subsections. We start by presenting our general model and its connections to other modeling approaches. We then present a simplified version of the model and discuss our strategy for the identification of the model parameters. We continue by presenting the elicitation methods used to determine the different parameters of the model. Finally, we discuss our econometric estimation approach.

2.2.1 A unified time-risk preference framework

We consider agents facing choices involving risk and time. Consequences of choices are streams of monetary outcomes $\boldsymbol{x} = (x_0, x_1, ..., x_T)$, where x_t is received at time t and T indicates a fixed time horizon. Objects of choice, called *risk-time prospects*, are probability distributions over streams of outcomes, i.e. $\boldsymbol{p} = (p_1, \boldsymbol{x_1}; ...; p_n, \boldsymbol{x_n})$, where $\boldsymbol{x_i} = (x_{i0}, ..., x_{iT})$. Uncertainty is always resolved immediately in our setup. For the sake of simplicity, a prospect giving $\boldsymbol{x}$ for sure is also denoted by $\boldsymbol{x}$. The set of objects of choice is endowed with a preference relation $\succcurlyeq$, with $\sim$ and $\succ$ defined as usual. This relation is assumed to be transitive and complete. In the sequel we assume without loss of generality that $\boldsymbol{x_1} \succcurlyeq ... \succcurlyeq \boldsymbol{x_n}$.

Under DEU, a risk-time prospect $\boldsymbol{p}$ is assigned the value

$$DEU(\boldsymbol{p}) = \sum_{i=1}^{n} p_i \sum_{t=0}^{T} D(t) u(x_{it}), \tag{2.4}$$

where u is a utility function defined from $\mathbb{R}$ to $\mathbb{R}$, which is unique up to a positive linear transformation, and D represents a discount function, i.e. a strictly decreasing function from nonnegative

numbers to the unit interval, with $D(0) = 1$. Note that Eq. (2.1), $D(t) = \phi^{-1}(p)$, results from the application of Eq. (2.4) to the indifference $(x, p) \sim (x, t)$.

We now amend the model given in Eq. (2.4) to allow for domain-specific utility and nonlinear probability weighting. We call this model generalized discounted expected utility ($GDEU$):

$$GDEU(\boldsymbol{p}) = \sum_{i=1}^{n} \pi_i \phi \left[\sum_{t=0}^{T} D(t) v(x_{it}) \right], \tag{2.5}$$

where π_i is a decision weight replacing the probability p_i, which is defined as follows: $\pi_i = w(\sum_{j=1}^{i} p_j) - w(\sum_{j=1}^{i-1} p_j)$. The weighting function w is a strictly increasing function on the unit interval satisfying $w(0) = 0$ and $w(1) = 1$. The component v stands for a utility function defined over temporal outcomes. The function ϕ is defined from $v(\mathbb{R})$ to $\mathbb{R}$, and is a strictly increasing and continuous transformation function. For fixed utility v the transformation ϕ is defined up to an increasing linear transformation. Additionally, the utility v can be replaced by $av + b$ if $\phi(.)$ is replaced by $\phi((. - b)/a), a > 0, b \in \mathbb{R}$.

We now discuss three different subcases of this model—DU, rank-dependent utility (RDU), and DEU with a domain-dependent utility. We start from DU. Assume that z (i.e. the stream $z_0\mathbf{0}$) is the present equivalent of a stream of outcomes $\boldsymbol{x} = (x^0, ..., x^T)$, i.e. the amount paid out at time 0 that the agent considers equally good as obtaining the stream $(x^0, ..., x^T)$. Further assume without loss of generality that $v(0) = 0$. Under GDEU $\phi[v(z)]$ is equal to $\phi\left[\sum_{t=0}^{T} D(t) v(x_t)\right]$. Given that ϕ is strictly increasing this simplifies to

$$v(z) = \sum_{t=0}^{T} D(t) v(x_t), \tag{2.6}$$

which is DU with v as a utility function. In our model v thus captures the utility of riskless temporal outcomes.

Let us now consider the RDU restriction of our model. Assume a risk-time prospect $\boldsymbol{p}$ such that $\boldsymbol{p} = (p_1, \boldsymbol{x_1}; ...; p_n, \boldsymbol{x_n})$, where $\boldsymbol{x_i} = (x_{i0}, 0, ..., 0),\ i = 1, ..., n$. That is, only the outcome received at $t = 0$ may be different from 0. Assuming again $v(0) = 0$ we obtain $GDEU(\boldsymbol{p}) = \sum_{i=1}^{n} \pi_i \phi\left[v(x_{i0})\right]$. Defining utility for risk as $\phi \circ v$, the equation above results in the standard RDU model.

Finally, we consider a version of our model where linearity of utility in the probabilities holds, but ϕ is not necessarily the identity function. This results in

$$GDEU(\boldsymbol{p}) = \sum_{i=1}^{n} p_i \phi \left[\sum_{t=0}^{T} D(t) v(x_{it}) \right], \tag{2.7}$$

This equation shows that accounting for the discrepancy between riskless intertemporal utility and

risky utility through ϕ necessarily impacts both utility *and* discounting.

In the absence of nonlinear probability weighting our preference functional is formally similar to the recursive model initially proposed by Kreps and Porteus [1978] and the preference functional used in the smooth ambiguity model by Klibanoff, Marinacci, and Mukerji [2005]. In Kreps and Porteus [1978], the ϕ reflects delayed resolution of uncertainty, while in Klibanoff et al. [2005] it reflects ambiguity attitudes. In our model, where no delayed resolution of uncertainty is at play, ϕ reflects the impact of immediately resolved risk on time preferences.

2.2.2 Model component identification in a simplified setup

To identify the parameters of our model, we elicit three quantities in a simplified choice context: risk equivalents (*REs*), certainty equivalents (*CEs*), and time equivalents (*TEs*). We restrict ourselves to binary prospects defined over streams of at most two outcomes. This requires simplified notation. If the agent receives a single future outcome at some date t, in the general setup the resulting stream can be written as $(0, ..., x_t, ..., 0)$, for which we will use the shorthand x_t. By the same token, a notation $y_s x_\ell$ represents a stream of two outcomes where x is received *s*ooner after a delay s and y is received *l*ater after a delay ℓ, and all other outcomes of the stream are equal to 0. A risk-time prospect is then defined as $(x_s x'_\ell, p; y_s y'_\ell)$, where the stream $x_s x'_\ell$ obtains with a probability p, and the the stream $y_s y'_\ell$ obtains with a complementary probability $1 - p$.

Risk equivalents

A RE corresponds to a probability that makes an agent indifferent between the risky prospect, $(x_s, p; 0)$, that gives x with probability p or else 0 at time s, and the temporal prospect $(x_\ell, 1; 0)$, which gives the *same* outcome x for sure at time ℓ. In the introduction, we considered the special case in which $s = 0$ for illustrative purposes. Under GDEU and after normalizing utility of the given outcome x, i.e. $v(x) = 1$, this indifference implies[8]

$$w(p)\phi[D(s)] = \phi[D(\ell)]. \tag{2.8}$$

Note that in case $s = 0$ and $\ell > 0$, as in the example of the introduction, this equation simplifies to $D(\ell) = \phi^{-1}[w(p)]$ under GDEU and to $D(\ell) = p$ under DEU. While the latter equation can be

[8]The general equation is $w(p)\phi[D(s)v(x)] = \phi[D(\ell)v(x)]$. Since we use a fixed outcome x (except for a consistency check not included in the main estimations), we can normalize the utility function. A parametric specification of ϕ as a power funtion, as used in the present paper, leads to the same result without a need for normalization.

fully identified from REs, the general Eq. (2.8) requires ϕ and w to be identified. This is achieved by eliciting CEs and TEs.

Certainty equivalents

A CE consists of a sure amount c_0 that the agent considers equally good as a two-outcome prospect $(x_0, p; y_0)$, where $x > y$. Under GDEU, this results in

$$\phi[v(c)] = w(p)\phi[v(x)] + (1 - w(p))\phi[v(y)]. \tag{2.9}$$

By obtaining such indifferences for different values of p and different outcomes x and y, we can identify both w and $u = \phi \circ v$. To separately identify ϕ and v we use TEs.

Time equivalents

Assume three outcomes y, y', and x. A TE received at time s is the outcome z such that $z_s y'_\ell \sim y_s x_\ell$. If $s = 0$ and $y' = 0$, the time equivalent is called a present equivalent. In other words, the PE of a stream of monetary outcomes, $y_s x_\ell$, is defined as the outcome $z \in \mathbb{R}$ such that $z_0 \sim y_s x_\ell$. That is, z is the outcome paid immediately (at $t = 0$) that the agent considers equally good as obtaining the stream of outcomes $y_s x_\ell$. In terms of GDEU, this indifference implies

$$D(s)v(z) + D(\ell)v(y') = D(s)v(y) + D(\ell)v(x). \tag{2.10}$$

This equation allows us to identify v and D under DU. Regarding the latter, taking this equation separately allows us to empirically test whether discounting obtained under risk using REs is the same as discounting obtained trading off riskless outcomes. Having identified v, we can now also identify ϕ.

2.2.3 Experimental procedures and stimuli

We recruited 104 subjects (41% female) at the experimental laboratory of the Technical University Berlin, Germany, using ORSEE [Greiner, 2004]. The experiments were run in March and April 2016 and were conducted in individual interviews by four experimenters. On average, the interviews lasted one hour. Upon arrival, subjects were invited to sit down in front of a computer. They were

then shown a recorded video presenting the experimental instructions (available upon request). They were also given written instructions, included in the online appendix. After watching the video, reading the instructions, and asking any questions they still had, they were presented with five comprehension questions. Before starting the experiment, they furthermore answered two practice questions, during which the experimenter further clarified any remaining doubts.

Stimuli were grouped by type to avoid confusion, and both the order of blocks of stimuli (REs, CEs, TEs) and of stimuli within each block was randomized. The complete stimuli are shown in table 2.1. The headings of the table indicate the tradeoffs faced in our simplified notation. The stimuli are then described in the format of the headers, with an asterisk $*$ marking the dimension varying within the choice list. One stimulus of each type was repeated at a randomly selected moment, which allows us to test for the consistency of responses and helps identifying the error term in econometric estimations.

Table 2.1: Experimental stimuli

	REs			CEs			TEs		
NR	$(x_s, p; 0)$	$\sim$	$(x_\ell, 1; 0)$	c_0	$\sim$	$(x_0, p; y_0)$	$z_s x'_\ell$	$\sim$	$y_s x_\ell$
1	$(30_0, p^*; 0)$	$\sim$	$(30_1, 1; 0)$	c_0^*	$\sim$	$(10_0, 0.5; 0_0)$	$z_0^* 0_1$	$\sim$	$0_0 30_1$
2	$(30_0, p^*; 0)$	$\sim$	$(30_3, 1; 0)$	c_0^*	$\sim$	$(20_0, 0.5; 0_0)$	$z_0^* 0_3$	$\sim$	$0_0 30_3$
3	$(30_0, p^*; 0)$	$\sim$	$(30_6, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.5; 0_0)$	$z_0^* 0_6$	$\sim$	$0_0 30_6$
4	$(30_0, p^*; 0)$	$\sim$	$(30_9, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.5; 10_0)$	$z_0^* 0_9$	$\sim$	$0_0 30_9$
5	$(30_0, p^*; 0)$	$\sim$	$(30_{12}, 1; 0)$	c_0^*	$\sim$	$(25_0, 0.5; 5_0)$	$z_0^* 0_{12}$	$\sim$	$0_0 30_{12}$
6	$(30_3, p^*; 0)$	$\sim$	$(30_6, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.1; 0_0)$	$z_3^* 0_6$	$\sim$	$0_3 30_6$
7	$(30_6, p^*; 0)$	$\sim$	$(30_9, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.3; 0_0)$	$z_6^* 0_9$	$\sim$	$0_6 30_9$
8	$(30_9, p^*; 0)$	$\sim$	$(30_{12}, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.7; 0_0)$	$z_9^* 0_{12}$	$\sim$	$0_9 30_{12}$
9	$(30_{11}, p^*; 0)$	$\sim$	$(30_{12}, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.9; 0_0)$	$z_{11}^* 0_{12}$	$\sim$	$0_{11} 20_{12}$
10	$(20_0, p^*; 0)$	$\sim$	$(20_6, 1; 0)$	c_0^*	$\sim$	$(30_0, 0.95; 0_0)$	$z_0^* 0_6$	$\sim$	$0_0 20_6$
11	$(20_0, p^*; 0)$	$\sim$	$(20_6, 1; 0)$				$z_0^* 10_6$	$\sim$	$10_0 30_6$
12							$z_0^* 20_6$	$\sim$	$0_0 30_6$
13							$z_0^* 20_6$	$\sim$	$10_0 30_6$
14							$z_0^* 20_6$	$\sim$	$20_0 30_6$

NOTE: All outcomes are in euros. At the time of the experiment, €1 $\simeq$ \$1.20; time delays are indicated in months

Subjects faced a total of 11 unique RE tasks. All but two (NRs 10 and 11), used for a consistency check, offered a fixed outcome of €30. The REs varied either the sooner time s or the later time ℓ. The main difference of CEs from REs was that a sure outcome was varied instead of the probability. CEs could vary between the high amount x and low amount y of the risky prospect, and the time of payout was always fixed at $s = 0$. Half of the prospects kept outcomes fixed at €30 or else 0, and varied probabilities from 0.1 to 0.9. We used one additional probability of 0.95 to take account of choices skewed towards high probabilities in REs revealed in a pilot. In the second half of the risky prospects we kept the probability fixed at 0.5 while varying the outcomes x and y. For TEs we again followed similar procedures. Just as for CEs, we varied sure monetary amounts in a choice list, while time periods and other outcomes were fixed. The elicited amount was always paid out

at the sooner period s. In 8 TEs we elicited indifferences between a sooner outcome and one later outcome fixed at €30. What varied between these lists were the sooner and later time period. In the remaining 6 TEs, the time periods were fixed at $s = 0$ and $\ell = 6$ months. The prospects contained a richer outcome space to identify intertemporal utility. The outcome y_s was introduced so as to obtain natural limits for the choice lists on which z_0^* was measured.

Figure 2.1 shows a screenshot of a RE task. It represents a choice between a 20% probability of receiving €30 in three months, or receiving €30 for sure in 6 months. The probability of winning in the risky prospect ranged from 0 to 1 in steps of 0.01. In order to speed up the decision process, a bisection procedure was used to complete the list. Once the list had thus been completed, subjects were forced to check and validate the complete choice list. At this point, they could alter their choices if desired before confirming the list and moving on to the next task. Subjects were explicitly made aware that the bisection procedure was merely a decision aid, and that final payoffs would be determined by the complete underlying choice list. Similar displays were used for CEs and TEs (see instructions in online appendix).

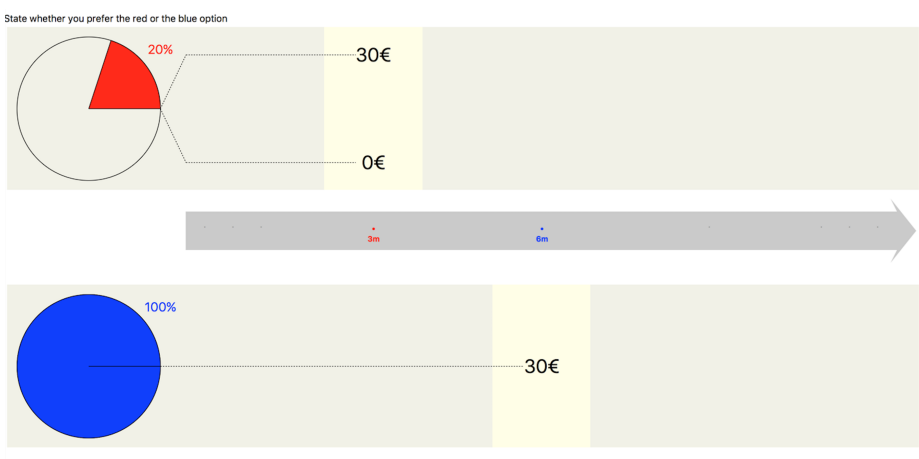


Figure 2.1: Screenshot of a RE task

All subjects obtained a €5 show-up fee, which was paid in cash after the experiment. In addition, subjects were incentivized by paying one decision randomly selected from all the choices with equal probability—the standard procedure in this type of experiment. The extraction always took place directly after the experiment, and any uncertainty was resolved at that point. The performance-contingent payments happened exclusively by bank transfer to equalize transaction costs between sooner and later payments. Subjects were made aware that the wire transfer of the early outcome would be made the following day and that the money would arrive on their account three days after that. By the same token, any payout indicated at time ℓ meant that the wire

transfer would be post-dated to that day, with the money arriving three days after the indicated time. The subjects obtained a certificate from the WZB Berlin Social Science Center, guaranteeing the delayed payoff. Subjects were familiar with the WZB, which maintains the experimental lab together with the Technical University. The certificate described the procedure, and contained information on the payment (amount and date of wire transfer), as well as contact numbers and emails of the administrators at the WZB making the transfer. Subjects were explicitly encouraged to contact the WZB in case they had any problems, or in case they were to change their bank account number before the payout date.

2.2.4 Econometric approach and parametric specifications

All the stimuli involve equivalences, either REs, CEs or TEs, measured by choice lists. We obtain a *predicted equivalent*, $\hat{q}$, for a given prospect $\boldsymbol{p}$. The predicted equivalent will be a function of the prospect $\boldsymbol{p}$ and of the vector of all model parameters $\boldsymbol{\omega}$, indicated as $\hat{q}(\boldsymbol{p},\boldsymbol{\omega})$. The predicted *time* equivalent, $\hat{q}_t(\boldsymbol{p},\boldsymbol{\omega})$, takes the following form

$$\hat{q}_t(\boldsymbol{p},\boldsymbol{\omega}) = v^{-1}\left[\frac{\delta_\ell}{\delta_s}\left(v(x) - v(x')\right) + v(y)\right] \tag{2.11}$$

We implement intertemporal utility v as a power function with constant elasticity of substitution (*CES*), where $v(x) = x^\theta$. The CES function is the most popular function in the literature [Brown and Kim, 2014, Miao and Zhong, 2015] , as well as being convenient to work with in the present setup.

The predicted *certainty* equivalent, $\hat{q}_c(\boldsymbol{p},\boldsymbol{\omega})$, will take the following form

$$\hat{q}_c(\boldsymbol{p},\boldsymbol{\omega}) = (\phi \circ v)^{-1}\left[w(p)\left(\phi[v(x)] - \phi[v(y)]\right) + \phi[v(y)]\right] \tag{2.12}$$

We again need to specify parametric forms for our function. Following the approach taken for v, we will implement ϕ as a power function, and designate the power parameter by γ. This means that $\phi \circ v$ will also follow a power specification, with a parameter $\rho = \gamma\theta$. For the probability weighting function w we adopt the one-parameter function proposed by Prelec [1998]:

$$w(p) = exp(-(-ln(p))^\alpha) \tag{2.13}$$

In our aggregate data, we cannot reject the hypothesis that the one-parameter function performs as well as the two-parameter formulation ($\chi^2(1) = 0.37, p = 0.544$, likelihood ratio tests). At

the individual level, the 2-parameter formulation outperforms the one-parameter formulation only for 29 subjects. Since the 2-parameter version generates outliers due to collinearity between the pessimism parameter and utility, we adopt the 1-parameter function also at the individual level.

Finally, the predicted *risk* equivalent, $\hat{q}_r(\boldsymbol{p}, \boldsymbol{\omega})$, will take the following form

$$\hat{q}_r(\boldsymbol{p}, \boldsymbol{\omega}) = w^{-1}\left[\frac{\phi(\delta_\ell)}{\phi(\delta_s)}\right], \tag{2.14}$$

where the righthand side is now transformed by the inverse of the weighting function, w^{-1}, since the predicted outcome takes the form of a probability.

In our data, we have an *observed equivalent*, q, which may be different from the theoretically predicted equivalent, $\hat{q}$, due to errors in responses or model mis-specifications relative to the true underlying decision process. To account for this, we add an error term to the predicted equivalent, such that $q = \hat{q} + \epsilon$, where ϵ is assumed to be a normally distributed error with mean 0 and variance σ^2, $\epsilon \sim \mathcal{N}(0, \sigma^2)$ [Hey and Orme, 1994]. To allow for heteroscedasticity, we estimate one error term for each prospect type, with standard deviations σ_t for TEs, σ_c for CEs, and σ_r for REs. We furthermore make σ_c proportional to the outcome range in a choice list [Bruhin et al., 2010], which provides a significantly better fit to our data than the homoscedastic version ($z = 35.75, p < 0.001$, Vuong [1989] test)[9]. No such adjustment is needed for σ_r, since q_r is naturally contained in the probability interval. As to σ_t, a formulation allowing for heterscedasticity by the choice list range is rejected in favor of a homoscedastic formulation ($z = -115,54, p < 0.001$, Vuong test), which we thus adopt.

We use maximum likelihood estimation to obtain our parameter values. Since our equivalents are measured in choice lists, we obtain interval information on each equivalent q. That is, we know that the true equivalent falls somewhere in the interval of outcomes between which a subject switched between prospects, but not exactly where in the interval it falls. To reflect this in our econometric approach, we define a lower bound q^- and an upper bound q^+ for our equivalent q, such that $q^- \leq q \leq q^+$. The cumulative probability distribution function, Π, associated with a given choice will then be

$$\Pi(\boldsymbol{p}, \boldsymbol{\omega}) = P(q^- \leq q \leq q^+) = P(q^- - \hat{q} \leq \epsilon \leq q^+ - \hat{q}) = \Phi(\frac{q^+ - \hat{q}}{\sigma}) - \Phi(\frac{q^- - \hat{q}}{\sigma}) \tag{2.15}$$

where P indicates the probability of q falling into a given interval, and Φ designates the cumu-

[9] A nonparametric Clark test results in the same qualitative conclusion; unless there are differences between the two tests, this will not be further mentioned.

lative normal distribution function. The formulation in terms of upper and lower bounds on the probability function has the advantage that it explicitly deals with corner solutions, i.e. subjects who consistently chose one and the same option in a choice list. The resulting log likelihood, LL, obtains by taking logs and summing over prospects

$$LL(\boldsymbol{p}, \boldsymbol{\omega}) = \sum_{i=1}^{N} \log \left[\Pi_i(\boldsymbol{p}, \boldsymbol{\omega})\right] \tag{2.16}$$

where Π_i represents the cumulative probability function for prospect i from Eq. (2.15). We estimate this likelihood at the individual level using the BFGS algorithm.

2.3 Results

We report the results in several steps. We start by reporting nonparametric data on discounting obtained from REs assuming DEU in section 2.3.1. In section 2.3.2 we compare discount factors obtained from REs under risk to riskless discount factors obtained from TEs, again under DEU. Section 2.3.3 zooms in on the utility dimension, and tests whether different utilities are needed under risk and over time. In section 2.3.4 we correct the discount factors obtained from REs for risk preferences (domain-dependent utility and nonlinear probability weighting), and compare the corrected discount factors to those obtained from TEs. Finally, in section 2.3.5 we test for deviations from exponential discounting.

2.3.1 The discount function for risk-time prospects under DEU

We begin by describing the REs obtained for different delays from $s = 0$ assuming DEU. Figure 2.2 displays the discount factors together with their interquartile range. The resulting discount function slopes downward as one would expect. The implied annualized discount factors, however, are found to increase in the length of the delay (i.e., annualized discount rates are lower the longer the delay). For instance, the median annualized discount factor for a 3 months delay from the present is 0.72 (corresponding to an annual discount rate of 40%), while the discount factor for a one year delay is 0.85 (corresponding to an annual discount rate of 18%). Indeed, all annualized discount factors derived from shorter delays are significantly smaller than discount factors derived from longer delays (all pairwise differences are significant at $p < 0.001$, using a Wilcoxon signed

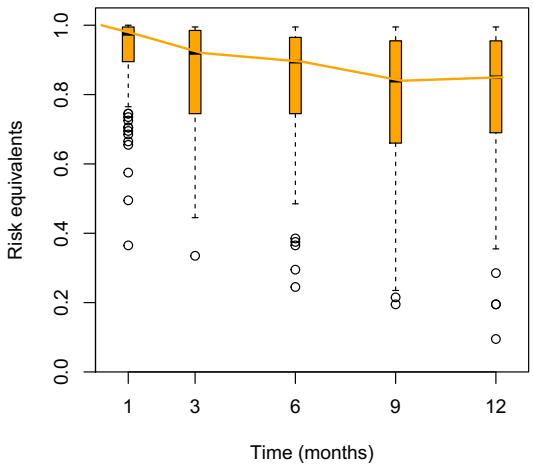


Figure 2.2: REs for time delays from $s = 0$

rank test).[10] This is consistent with earlier findings showing that lower discount rates are estimated for longer time delays [Read, 2001].

We next examine issues of stationarity, i.e. whether discounting is constant over time or follows different patterns such as decreasing (or potentially increasing) impatience. Table 2.2 shows pairwise comparisons of risk equivalents elicited for three months delays from different starting periods, indicated as $p(s, \ell)$. The table indicates the number of subjects with larger REs for the earlier period (increasing impatience), with equal REs for the two periods (constant impatience), and with smaller REs for the earlier period (decreasing impatience). Compared to the 3 months delay from $s = 0$ (shown in the first three data columns of the table), about one third of subjects can be seen to have constant discount rates, with this rate slightly declining in the initial delay of the comparison prospect. Of the remaining two thirds, a majority exhibits larger discount factors as the up front delay increases, indicating decreasing impatience. This asymmetry is highly significant as indicated by the Wilcoxon signed rank tests reported in the last row of the table. Nonetheless, there is also a substantial minority of subjects (hovering around 20% of our sample) who exhibit *increasing* impatience [Attema, Bleichrodt, Rohde, and Wakker, 2010].

These patterns tend to be much weakened when comparing the three months periods starting in 3 months or 6 months to later up front delays, as shown in the last three data columns of table

[10] Two delays, of 6 months and 12 months from the present, where included using lower stakes of €20 as a stability check. Using these two tasks, we find the same qualitative pattern of annualized discount factors increasing in the delay, with an annualized discount factor of 0.79 for the 6 months delay, and a discount factor of 0.85 for the 12 months delay (different at $p < 0.001$, signed rank test).

Table 2.2: Classification of time inconsistencies

versus	$p(3,6)$	$p(0,3)$ $p(6,9)$	$p(9,12)$	$p(3,6)$ $p(6,9)$	$p(3,6)$ $p(9,12)$	$p(6,9)$ $p(9,12)$
$p(s,\ell) > p(s+k,\ell+k)$	23	19	22	25	26	29
$p(s,\ell) = p(s+k,\ell+k)$	38	34	29	40	37	43
$p(s,\ell) < p(s+k,\ell+k)$	43	51	53	39	41	32
signed-rank test	$z = -3.00$ $p = 0.003$	$z = -4.07$ $p < 0.001$	$z = -4.13$ $p < 0.001$	$z = -1.63$ $p = 0.104$	$z = -2.01$ $p = 0.045$	$z = -0.40$ $p = 0.686$

2.2. The number of time consistent subjects, indicating the same REs for different 3 months delays, is somewhat larger than in comparisons to 3 months delays from the present. And although there is still some asymmetry towards decreasing impatience, this pattern is now much weaker than in comparisons to delays from the present, with only the comparison of the 3 months delay starting in 3 months or in 9 months significant at conventional levels. This provides a first indication that generalized hyperbolicity is rather weak in our data at the aggregate level, while quasi-hyperbolic behavior tends to be stronger.

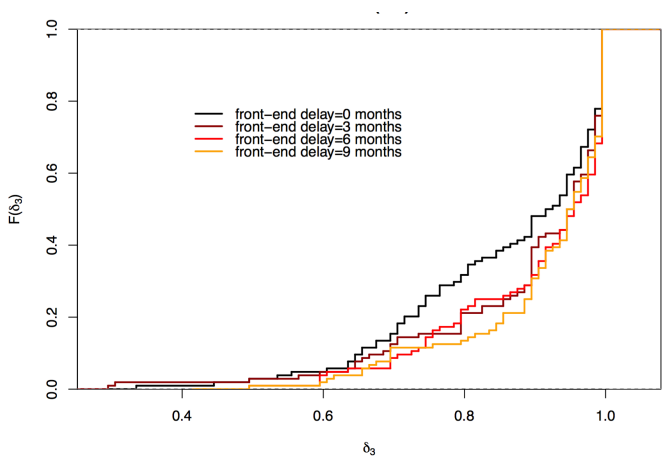


Figure 2.3: Cumulative distribution functions for 3-months delays

We further investigate this issue in figure 2.3, which shows the cumulative distributions for 3 months delays from different initial times. The CDF for the three months delay from $s = 0$ clearly stands out from the others, with people switching to the risky prospect at lower winning probabilities. The CDFs for other delays are much closer together, and differences are more difficult to spot, again suggesting a quasi-hyperbolic pattern rather than a fully hyperbolic one in the aggregate data.

Finally, we can take a look at some typical patterns occurring at the individual level, shown in figure 2.4. These are derived by taking the ratio of later 3-month delays relative to a 3-months delay

from the present, $p(s,s+3)/p(0,3)$, where $s = 3, 6, 9$. With the initial discount factor normalized to 1 in the graph, changes in the index can then be taken as a direct measure of stationarity. In particular, a horizontal line indicates constant discounting, an upward sloping line decreasing impatience, and a downward sloping line increasing impatience.

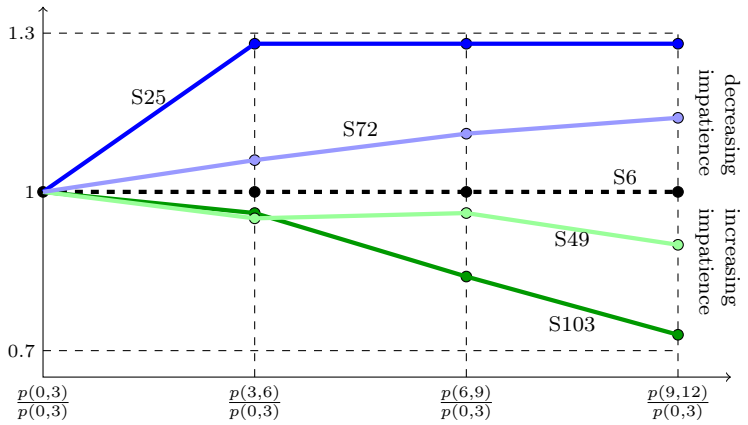


Figure 2.4: Hyperbolicity at the individual level: examples

The horizontal dashed line indicates constant discounting, which is exhibited by subject 6 and many others (as well as being the median pattern in the data). Subject 25 exhibits a quasi-hyperbolic pattern—there is decreasing impatience in the first segment, with stationarity prevailing thereafter. Subject 72 shows fully hyperbolic behavior, with a curve that slopes upward for each subsequent delay. Finally, subjects 49 and 103 show the opposite of hyperbolic behavior, i.e. they show increasing impatience. Impatience is strongly increasing for subject 103, with each subsequent comparison resulting in a increase in impatience. Subject 49 exhibits something closer to the opposite of quasi-hyperbolic behavior, with impatience registering in the first comparison and then staying approximately level. Clearly, these are but a few examples of behavior and other patterns exist, including more erratic ones.

2.3.2 Risky versus riskless discounting under DEU

We now compare discount factors derived from REs and involving risk to riskless discount factors derived from TEs. We assume DEU throughout this section—corrections of risky discounting for risk preferences in the generalized model will be discussed in section 2.3.4. Under the DEU assumption, there is indeed no reason to expect discounting to differ systematically between risky and riskless environments. Figure 2.5 shows the comparative discount factors for the different delay

periods in our data derived from REs and TEs. The discount factors shown are based on maximum likelihood estimations which include intertemporal utility v for TEs to make them fully comparable to discount factors obtained from REs (i.e., the estimations of discount factors from TEs are based on Eq. (2.11)). Utility itself will be discussed in the next section.

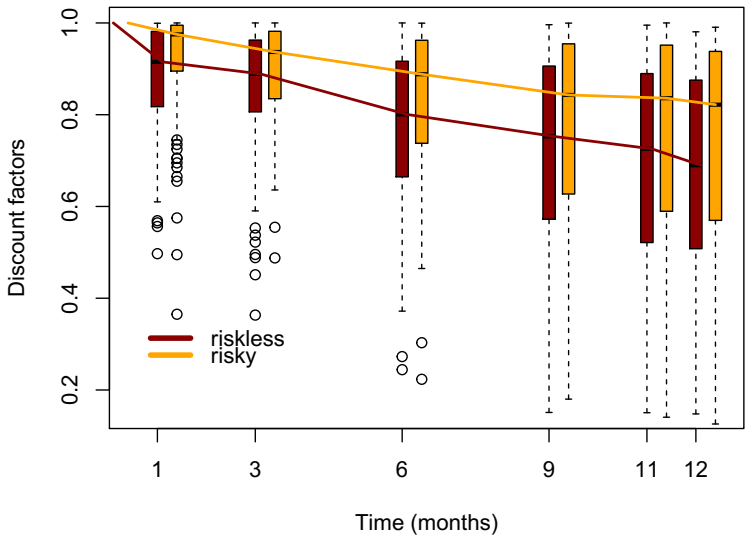


Figure 2.5: Discount factors for REs and TEs under DEU

It is easy to discern that the median discount factors obtained from riskless TEs are always smaller than those obtained from REs. In other words, discounting appears to be more severe when elicited under certainty than when elicited under risk. This provides a first indication that risk indeed has an impact on discounting, as postulated by our GDEU model. This in turn means that DEU is violated in our data. It also appears that the difference between risky and riskless discounting increases with the time delay, suggesting an effect on discount rates and not only on hyperbolicity.

Table 2.3 provides summary statistics of the different discount factors estimated under risk and under certainty and tests of their equality. The median discount factor can be seen to be lower in the riskless setup than in the risky one in all cases. This difference is indeed significant in all cases using either a Wilcoxon signed-rank test or a sign test on positive versus negative deviations. It remains statistically significant in all cases also when applying a Bonferroni adjustment, which requires p-values of 0.008 or smaller to account for the fact that the six tests are not independent of each-other. The difference is also economically important. For instance, the discount factor for

Table 2.3: Discount factors under risk and under certainty assuming DEU

	Risky		Riskless		Comparison		
	Median	IQR	Median	IQR	Wilcoxon test	Sign test	Spearman Correlation
δ_1	0.97	[0.89 ; 0.99]	0.91	[0.81 ; 0.97]	-3.60***	74/30***	0.36***
δ_3	0.94	[0.84 ; 0.98]	0.88	[0.80 ; 0.95]	-2.99**	66/38**	0.60***
δ_6	0.89	[0.74 ; 0.96]	0.79	[0.64 ; 0.91]	-4.64***	74/30***	0.69***
δ_9	0.84	[0.63 ; 0.95]	0.74	[0.56 ; 0.88]	-4.01***	74/30***	0.68***
δ_{11}	0.83	[0.59 ; 0.95]	0.72	[0.57 ; 0.88]	-3.79***	74/30***	0.62***
δ_{12}	0.82	[0.57 ; 0.94]	0.68	[0.56 ; 0.84]	-3.93***	74/30***	0.64***

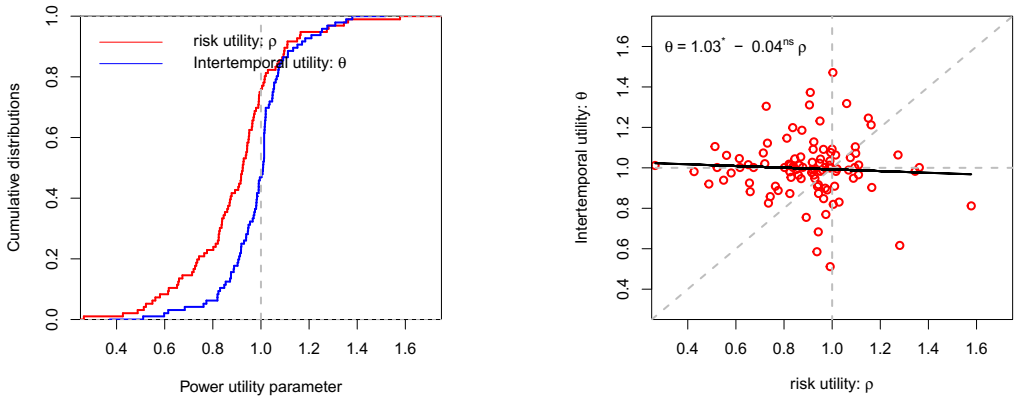
p-values in parentheses; all p-values reported are two-sided; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

a 12 months delay elicited under risk is equal to 0.82, corresponding to a yearly discount rate of 22%. The equivalent discount factor for a 12 months delay elicited from TEs under certainty is 0.68, corresponding to a yearly discount rate of 47%—more than double the discount rate estimated under risk. Beyond these differences, however, we also find the discount factors to be significantly correlated in all cases, indicating that they are capturing one and the same behavioral trait. These correlations are indeed strong, with the exception of the one month delay, where the correlation is only moderate to weak.

2.3.3 Utility under risk and utility over time under GDEU

We now abandon the DEU assumption and move on to testing our generalized model. The first step will be to test for utility differences between choices over time and under risk. We assume CES utility functions for risk and time, i.e. $u(x) = x^\rho$ and $v(x) = x^\theta$[Epstein and Zin, 1989, Miao and Zhong, 2015], and estimate θ from Eq. (2.11) and ρ from Eq. (2.12). The equality of the power coefficients of the two utility functions under risk and time, $\rho = \theta$, is clearly rejected in our data ($z = -2.953, p < 0.001$; Wilcoxon signed-rank test), with median values of $\rho = 0.93$ and $\theta = 1.01$. Inter-temporal utility is thus different from risky utility, in violation of DEU and as predicted by GDEU. Indeed, we cannot reject the hypothesis that inter-temporal utility is linear ($z = -0.170, p = 0.864$; Wilcoxon signed-rank test). Risky utility, on the other hand, shows significant concavity ($z = -5.228, p < 0.001$; Wilcoxon signed-rank test).

Figure 2.6 compares the distribution of the utility parameters for risk, ρ, and the utility parameter for time, θ. Panel 2.6a shows the cumulative distribution functions of the two utility parameters. For inter-temporal utility, we observe a large proportion of subjects having a parameter value close to 1. For risky utility, close to 60% of subjects have a parameter value below 0.9. Overall, there is thus a clear trend of more concave utility under risk than over time. Panel 2.6b shows a scatter



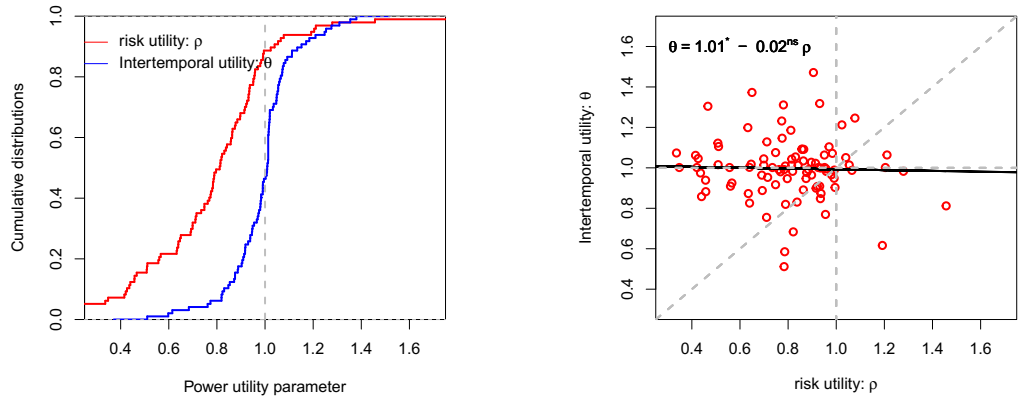
(a) CDF of utility parameters

(b) Utilies under risk and over time

Figure 2.6: Utility parameters under risk and over time

plot of the two utility parameters θ and ρ. The majority of the data points for the risky utility parameter ρ can be seen to be to the left of the dashed line at 1, indicating concave utility. For the intertemporal utility parameter θ, shown on the ordinates, there is no clear pattern, with about equally many points to either side of the dashed line indicating 1. The graph furthermore clearly shows that there is no correlation between inter-temporal and risky utility ($r_s = 0.07, p = 0.466$; Spearman rank correlation). These results are in agreement with earlier findings [Andreoni and Sprenger, 2012, Abdellaoui et al., 2013], and suggest that utility curavture under risk and intertemporal elasticity of substitution constitute independent behavioral characteristics.

We have so far considered our full GDEU model. There may, however, be some interest in considering the case of $w(p) = p$ instead, i.e. the generalized model without probability weighting. Indeed, estimating risky utility while imposing linearity in probabilities generally results in different utility estimates from the full model [Bleichrodt et al., 2007, Booij, Praag, and van de Kuilen, 2010]. Figure 2.7 depicts the utility functions under the EU modeling assumption, with panel 2.7a showing the cumulative distribution function of the two utility powers, and panel 2.7b showing a scatter plot. The results are qualitatively similar to those seen above, except that utility under risk is even more clearly concave ($z = -6.49, p < 0.001$; Wilcoxon signed-rank test), with a median parameter value of $\rho = 0.81$. The scatter plot once again reveals no significant correlation between the two utility parameters ($r_s = 0.051, p = 0.607$; Spearman correlation), thos contradicting the DEU assumption of intertemporal elasticity of substitution being the inverse of utiity curvature under risk.



(a) CDF of utility parameters

(b) Scatter plot of utility parameters

Figure 2.7: Utility parameters under risk and over time with linear probabilities

2.3.4 Correcting discounting for risk preferences

We have seen in the last two sections that risk counts—utility under risk is different from intertemporal utility in our data, and discount functions elicited under risk and in riskless environments differ systematically. We will now investigate whether adjusting discounting for risk preferences, as postulated by our generalized model, helps to close the gap between risky and riskless discounting. Figure 2.8 shows again the comparison of discount factors obtained from the risky and the riskless tasks as shown in figure 2.5, and further adds the risky discount factors corrected for risk preferences (i.e., corrected using ϕ and w according to Eq. (2.8)). The discount factors obtained under risk are generally lowered by the correction. This also means that the median corrected discount factors appear to fall much closer to the median discount factors obtained under certainty than the uncorrected discount factors obtained from risk equivalents.

Table 2.4 further provides summary statistics of the discount factors and tests for differences between the corrected risky discount factors and the riskless discount factors. The median discount factors can now be seen to be very similar for corrected risky and riskless measures. Indeed, only one pairwise comparison, for δ_{11}, of risky and riskless discounting is significant according to a Wilcoxon signed-rank test.[11] Using a Sign test, none of the pairwise comparisons result significant. This is furthermore before any adjustment for multiple testing are applied, with no test meeting

[11]The estimation of δ_{11} may be seen as generally less stable than the estimation of the other discount factors, inasmuch as it is identified purely from a comparison with $s = 11$ and $\ell = 12$, which was inserted for the identification of hyperbolic behavior in comparison to the 1 month delay from $s = 0$. This means that this discount factor is defined only in contrast to the 12 months discount factor, and is thus not fully independent.

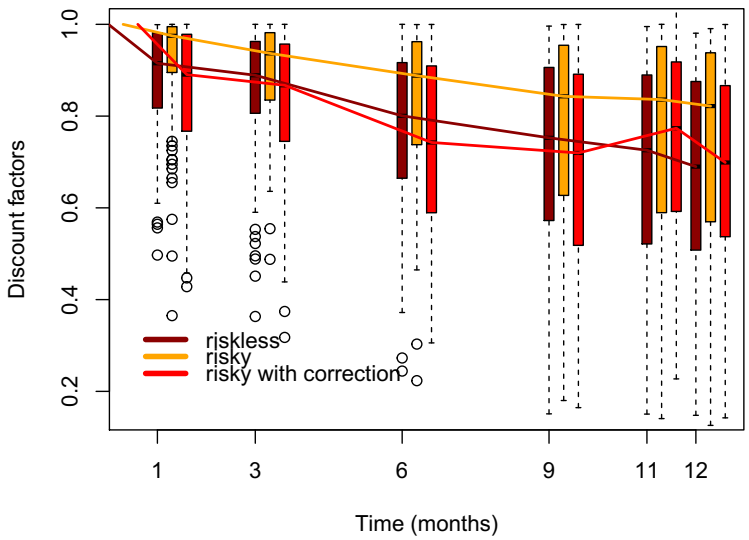


Figure 2.8: Discount functions under certainty, risk, and risk corrected for ϕ and w

the more stringent criterion of $p \leq 0.008$ required by Bonferroni adjustments. In other words, we cannot reject the hypothesis that the discount factors are the same once we correct discount factors obtained from REs for risk preferences using both ϕ and w. This stands in marked contrast to the finding for the uncorrected discount factors obtained from REs, which were found to be significantly larger than the riskless ones in all cases. The correlations between the discount factors remain generally strong and highly significant after the correction, and are of the same order of magnitude as observed before the correction.

Table 2.4: Statistics on discount parameters corrected by ϕ and w

	Risky corrected for ϕ and w		Riskless		Comparison		
	Median	IQR	Median	IQR	Wilcoxon test	Sign test	Spearman Correlation
δ_1	0.89	[0.77 ; 0.98]	0.91	[0.82 ; 0.98]	-1.518^{ns}	49/55^{ns}	0.376***
δ_3	0.87	[0.75 ; 0.96]	0.88	[0.80 ; 0.95]	-1.852^{ns}	44/60^{ns}	0.639***
δ_6	0.74	[0.59 ; 0.91]	0.79	[0.64 ; 0.91]	-1.414^{ns}	47/57^{ns}	0.652***
δ_9	0.72	[0.52 ; 0.89]	0.74	[0.56 ; 0.88]	-0.513^{ns}	52/52^{ns}	0.612***
δ_{11}	0.77	[0.59 ; 0.92]	0.72	[0.57 ; 0.88]	1.965^{ns}	58/46^{ns}	0.618***
δ_{12}	0.70	[0.54 ; 0.87]	0.68	[0.56 ; 0.84]	0.152^{ns}	55/49^{ns}	0.597***

p-values in parentheses; all p-values reported are two-sided; ***: $p < 0.001$; ns: non significant

To complete the picture on the effect of correcting discount factors elicited under risk for risk preferences, we can take a look at their distributions. Figure 2.9 shows the cumulative distribution

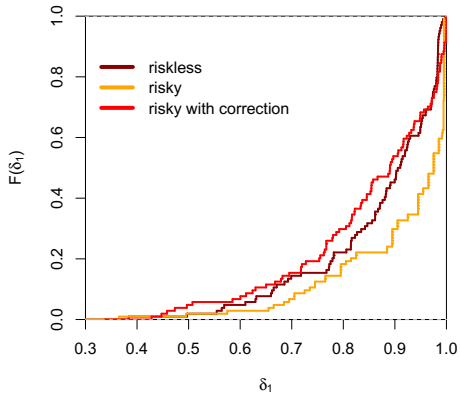
function of the six discount factors. Each panel compares the cumulative distribution function of the riskless discount factor to those of the uncorrected risky discount factor and the risky discount factor corrected for risk preferences. A common pattern emerges across the panels. Compared to riskless discounting obtained from TEs, the uncorrected discounting obtained from risky tradeoffs generally shows an accumulation of observations close to 1. Correcting risky discounting for risk preferences eliminates this accumulation close to 1, and pushes the distribution close to the one observed for riskless discounting.

An interesting question is whether we need our full model, or whether it is sufficient to estimate the model assuming that probabilities are treated linearly, i.e. $w(p) = p$. A boxplot comparing the risky discount factors corrected by ϕ under the assumption that $w(p) = p$ to the riskless discount factors and the uncorrected risky discount factors is shown in figure 2.10. Correcting the risky discount factors using ϕ clearly lowers them, making discounting more severe and hence closing the gap with riskless discount factors. At the same time, this correction does not go far enough, with discount factors under risk still being systematically larger than riskless discount factors even after applying the correction.

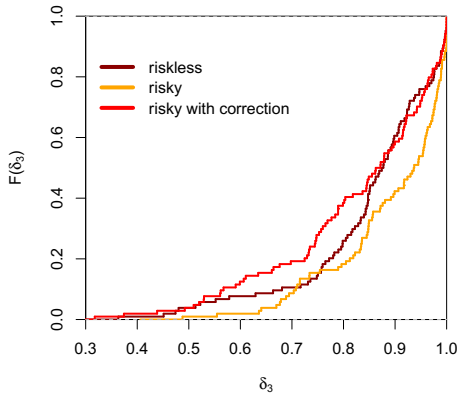
To see if this intuition gathered from the boxplot is indeed correct, table 2.5 presents summary statistics on the discount factors and tests their equality. The median discount factors can be seen to remain universally larger under risk than they are under certainty. This difference remains significant for three discount factors according to the signed-rank test (and marginally significant for two more), and for five out of six according to the sign test. This difference furthermore remains significant for two comparisons after applying Bonferroni adjustments according to the Wilcoxon test, and for fully five comparisons when applying the sign test. The difference also remains significant economically. The 12 months discount factor elicited in the absence of risk is 0.68, corresponding to a yearly discount rate of 47%. The corresponding discount factor obtained from the risky measure after correcting for ϕ is 0.74, corresponding to a yearly discount rate of 35%. Although the gap has narrowed somewhat relative to the case in which no correction was applied (where the yearly discount rate obtained from REs was 22%), there continues to be a sizable difference in estimated discount rates.

2.3.5 Patterns of discounting

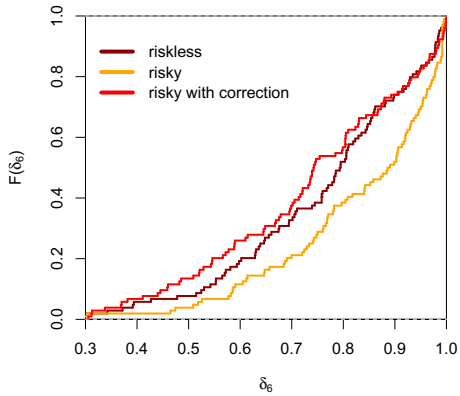
We now discuss the shape of discount functions. In keeping with the analysis above, we pursue a semi-parametric approach whereby we parametrically estimate only the correction factors v, ϕ, and



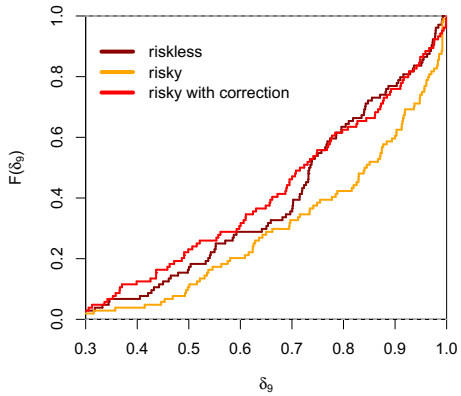
(a) CDF δ_1



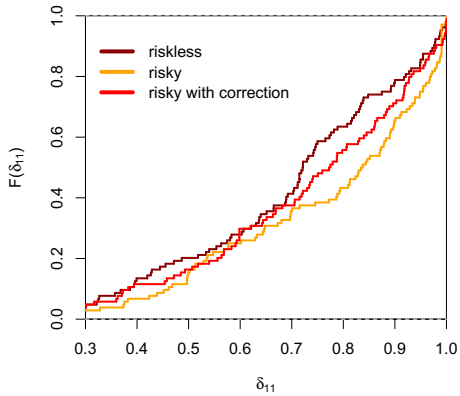
(b) CDF δ_3



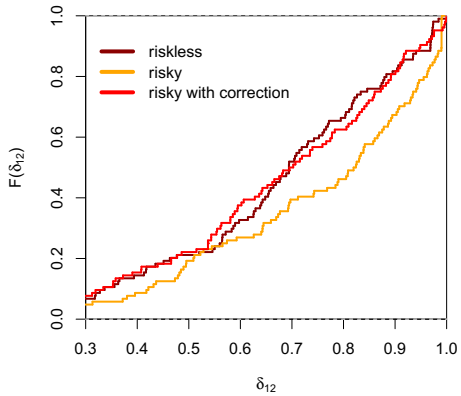
(c) CDF δ_6



(d) CDF δ_9



(e) CDF δ_{11}



(f) CDF δ_{12}

Figure 2.9: Cumulative distribution functions of discount factors, corrected and uncorrected

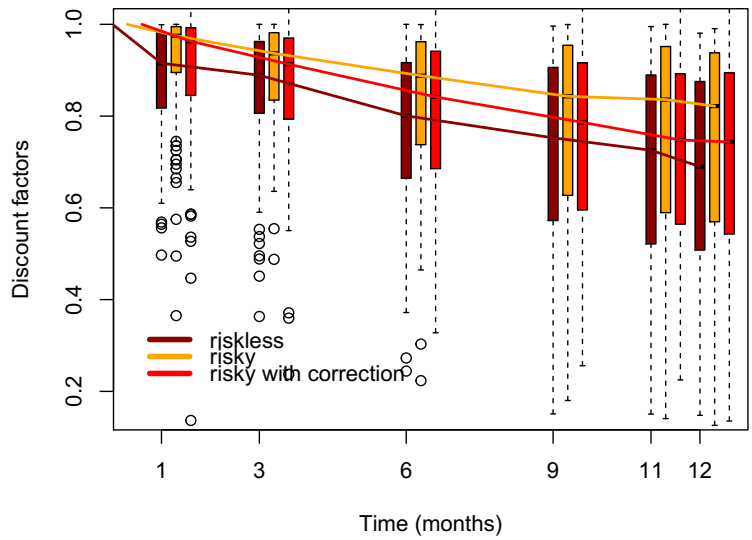


Figure 2.10: Discount functions under certainty, risk, and risk corrected for ϕ under $w(p) = p$

Table 2.5: Statistics on discount parameters corrected by ϕ assuming $w(p) = p$

	Risky corrected for ϕ		Riskless		Comparison		
	Median	IQR	Median	IQR	Wilcoxon paired test	sign test	Spearman Correlation
δ_1	0.96	[0.85 ; 0.99]	0.91	[0.81 ; 0.98]	-1.899 (0.058)	65/39 (0.007)	0.399 (<0.001)
δ_3	0.91	[0.80 ; 0.97]	0.88	[0.80 ; 0.94]	-1.159 (0.246)	59/45 (0.101)	0.630 (<0.001)
δ_6	0.84	[0.69 ; 0.94]	0.80	[0.65 ; 0.91]	-2.979 (0.003)	68/36 (0.001)	0.738 (<0.001)
δ_9	0.79	[0.60 ; 0.91]	0.74	[0.56 ; 0.89]	-2.298 (0.022)	65/39 (0.007)	0.742 (<0.001)
δ_{11}	0.75	[0.57 ; 0.89]	0.72	[0.51 ; 0.88]	-1.837 (0.066)	68/36 (0.001)	0.608 (<0.001)
δ_{12}	0.74	[0.54 ; 0.89]	0.68	[0.48 ; 0.85]	-2.638 (0.008)	69/35 (0.001)	0.656 (<0.001)

p-values in parentheses; all p-values reported are two-sided

w, while we base the analysis of the shape of discount functions purely on a nonparametric analysis of the discount factors. This is important inasmuch as imposing specific functional forms could distort discounting even after controlling for other potential distortions such as the one deriving from nonlinear utility. We will focus on riskless discounting and discounting under risk corrected as prescribed by the GDEU model, since we already have examined discounting under risk assuming DEU in section 2.3.1 in a fully non-parametric way.

We start by testing whether exponential discounting may be a good model. We test for hyperbolicity by comparing the discount factor estimated for a given delay $t + k$ to the discount factor estimated for the delay t, taken to the power $(t + k)/t$. For instance, the discount factor for $t + k = 6$ months is compared to the discount factor for $t = 3$ months, taken to the power

Table 2.6: Test of hyperbolicity

discount factors estimated from time equivalents							
δ_{t+k}	δ_{12}			δ_9		δ_6	
$\delta_t^{\frac{t+k}{t}}$	δ_1^{12}	δ_3^4	δ_6^2	δ_1^9	δ_3^3	δ_1^6	δ_3^2
$\delta_{t+k} > \delta_t^{\frac{t+k}{t}}$	89	69	75	89	78	91	61
$\delta_{t+k} < \delta_t^{\frac{t+k}{t}}$	15	35	29	15	26	13	43
signed-rank test	$z = 7.74$ $p < 0.001$	$z = 4.50$ $p < 0.001$	$z = 5.36$ $p < 0.001$	$z = 7.76$ $p < 0.001$	$z = 4.81$ $p < 0.001$	$z = 7.44$ $p < 0.001$	$z = 2.62$ $p = 0.009$
discount factors estimated from risk equivalents (corrected for ϕ and w)							
$\delta_{t+k} > \delta^{\frac{t+k}{t}}$	85	77	77	86	70	85	60
$\delta_{t+k} < \delta^{\frac{t+k}{t}}$	19	27	27	18	34	19	44
signed-rank test	$z = 7.33$ $p < 0.001$	$z = 5.81$ $p < 0.001$	$z = 6.07$ $p < 0.001$	$z = 7.17$ $p < 0.001$	$z = 4.50$ $p < 0.001$	$z = 6.99$ $p < 0.001$	$z = 3.03$ $p = 0.002$

$(t + k)/t = 2$. If discounting is exponential, the two should be identical. If we observe hyperbolic behavior, on the other hand, we would expect that $\delta_{06} > \delta_{03}^2$, indicating that discounting for a 6 months period extrapolated from the discount factor for the first 3 months overestimates the severity of discounting.

Table 2.6 shows the discount patterns for both time equivalents and corrected risk equivalents, as well as tests for the relative frequency of different types of behavior. The pattern based on the discount factors derived from time equivalents is very clear. In all cases the discount factors based on shorter time delays are smaller than the actual discount factors measured over the whole delay, indicating hyperbolic discounting. This does not, however, tell us whether the pattern we find is truly hyperbolic or quasi-hyperbolic, since all comparisons include the delay from $t = 0$. To address this issue, we can construct three months delays that are purified of the discounting of the initial period, by taking δ_{t+k}/δ_t, where k is equal to a 3 months delay. Comparing δ_6/δ_3 to δ_9/δ_6, we find that discounting is still considerably stronger in the earlier measure ($z = 4.26, p < 0.001$). This provides some evidence for truly hyperbolic behavior. Comparing δ_9/δ_6 to δ_{12}/δ_9, on the other hand, we find no significant difference ($z = -1.05$, p=0.295). While there is thus some evidence for strongly hyperbolic behavior, this evidence remains weak for later time delays and quasi-hyperbolicity seems to be the predominant pattern.

The discount factors obtained from risk equivalents paint a very similar picture to the one just seen for time equivalents. Just as seen for the latter, a clear majority of subjects displays larger discount factors for the longer delays than one would impute from the earlier delays. The similarity also carries over to the strength of hyperbolicity. Comparing δ_6/δ_3 to δ_9/δ_6, we once again find that discounting is still stronger in the earlier measure ($z = 2.18$, p=0.029). And once again, this

hyperbolic pattern disappears when comparing δ_9/δ_6 to δ_{12}/δ_9 ($z = 0.08$, p=0.93). We thus conclude that while there is clear evidence for some sort of hyperbolicity in the data, this seems mostly due to the earliest delays, likely indicating quasi-hyperbolicity. The evidence for strongly hyperbolic patterns is weaker, and furthermore seems to decline with longer time delays, disappearing for delays longer than 6 months.

2.4 Discussion and conclusion

While DEU inherits the normative appeal of both the DU and the EU models, it cannot formally distinguish intertemporal substitution and risk attitude. The necessity of such a distinction was empirically demonstrated via two approaches. The first consists in the separate elicitation of intertemporal substitution under DU and of the risky utility index under EU [Abdellaoui et al., 2013, Andreoni and Sprenger, 2012]. The second approach consists in using Epstein and Zin's [1989] recursive expected utility to elicit a domain-dependent utility index [Brown and Kim, 2014, Miao and Zhong, 2015]. These approaches indirectly posed the problem of investigating the combination of time and risk preferences within a simple setup where time is naturally connected with risk–a connection which is inherent to intertemporal tradeoffs (e.g. Fisher, 1930). For measurement purposes, it is desirable that such a setup allow for the detection of choice "anomalies" both over time and under risk. The present paper aims to satisfy this requirement using a time-risk extension of DEU where utility is domain-dependent, discounting is not necessarily exponential, and the agent can exhibit non-linear probability weighting under risk.

The risk equivalent method allows us to bypass the utility confound in the measurement of discounting under DEU [Frederick et al., 2002], and to thus access the discount function directly through the elicitation of matching probabilities. Comparing the discount factors thus obtained to discount factors obtained from riskless intertemporal tradeoffs, we found systematic differences between the two. One of the reasons for this may be differences between risky and intertemporal utility. While we indeed found the two utility functions to be different, thus confirming previous results, we also showed that this difference could not fully account for the difference in discounting. Correcting the discount factors obtained under risk for both utility differences and probability weighting, however, made the differences between the two disappear. This indicates the importance of combining utility differences ϕ and probability weighting w to account for the behavioral patterns

in the data.[12] Indeed, neglecting the difference between the two utility functions and/or probability weighting in the elicitation of discounting could lead to a biased estimate of discounting Abdellaoui, Attema, and Bleichrodt [2010], Andersen et al. [2008].

Our approach to the elicitation of discounting is semi-parametric in the sense that no parametric form was imposed on the discount function, i.e. only utility and probability weighting functions were assigned parametric forms. Using REs under DEU, our non-parametric analysis at the individual level showed about one third of subjects to exhibit constant discounting. The modal pattern for delays from the present, however, consisted in subjects exhibiting decreasing impatience. This tendency towards decreasing impatience declined markedly when comparing delayed consequences, indicating a quasi-hyperbolic rather than fully-hyperbolic pattern in the data. A sizable minority of subjects also exhibited the opposite pattern of increasing impatience [Attema et al., 2010]. Nor where these findings due to the use of risk equivalents under DEU alone. Indeed, we replicated the same type of (quasi-) hyperbolic patterns both with our corrected risk equivalents and with time equivalents obtained in riskless environments.

Our model's underlying psychological intuition is related to an intuition present in several recent papers. In particular, decisions involving tradeoffs under risk and over time have been found to result in remarkably similar violations of the two standard models of DU and EU by Prelec and Loewenstein [1991]. This seems to derive from the common intuition that both risk and time create psychological distance from the desired outcome [Dean and Ortoleva, 2016, Köszegi and Szeidl, 2013]. The latter, however, cannot provide an account of the difference between risky and riskless discount functions obtained in the present paper. We exploit this intuition in our experimental task by having subjects trade off the two elements of psychological distance against each other, thus naturally integrating risk and time in our design.

While we are not the first to account for probability weighting in intertemporal choice [Epper and Fehr-Duda, 2014, Halevy, 2008, Miao and Zhong, 2015], our work is the first to account for *both* domain-dependent utility and Allais-type behavior under risk. In situations where risk is explicitly mixed with intertemporal tradeoffs, such as the ones we investigate, utility has repeatedly been shown empirically to differ between risk and intertemporal tradeoffs. This makes the modeling of differences in utility across domains imperative. Nevertheless, our results have also shown that

[12] This result is consistent with the recent experimental findings in Dean and Ortoleva [2016]. The authors found a significant correlation between attitudes towards risk (as represented in our model by ϕ and w) and discount rates.

allowing for such differences in utility alone is not sufficient to account for differences in discounting between risky and riskless environments. To achieve that aim, allowing for both differences in utility and nonlinear probability weighting appears to be essential.

Trading off the time and risk dimensions against each other, we introduced an intuitive way to measure time preferences in a risky setup. This is important inasmuch as most real-world decisions involve both time and risk, while experimental measurement tasks used to date generally treated the two dimensions as separate. We also showed, however, that the measure of time preferences thus obtained is biased due to the violations of DEU. Applied researchers wanting to obtain a measure of time preferences that remains valid without having to assume discounted expected utility will thus need to apply a correction that is simpler to obtain than the one shown in this paper. As long as we are happy to only correct the discount factors at the aggregate level, this is easily achieved. In the online appendix, we show such a correction for our discount factors using aggregate estimations on the German data reported by L'Haridon and Vieider [2016]. After this correction, only one of the discount factors remains different at conventional levels according to a Wilcoxon test, and only two according to a sign test. Only the one difference based on the Wilcoxon test remains significant after applying a Bonferroni adjustment. This shows that it is possible to use aggregate estimates from the literature to achieve corrections at the aggregate level, at least as long as these estimations have been obtained in the same country and for comparable stake levels.

In terms of applications of the measures presented in this paper, it is important to internalize the observation that the uncertainty and time dimensions are naturally intertwined. In this sense our approach naturally emulates the uncertain nature of time. This also makes it crucial to account for both dimensions when obtaining measures meant to correlate with real world behavior, which will inevitably encompass both aspects of uncertainty and time delays. It also makes it essential to account for both dimensions when obtaining estimates of time preferences aimed at the calibration of theoretical models. Our risk equivalents constitute a straightforward way of measuring the two elements in conjunction. Obtaining correcting factors under risk as pointed out above will furthermore allow for the separation of the elicited attitudes into its component parts. Future research will tell to what extent the modeling and prediction of real world processes may be impacted by the natural integration of uncertainty and time we have proposed.

Chapter 3

God Insures Those Who Pay?

3.1 Introduction

Religious institutions fulfil important economic functions across the world. Certain market failures can be overcome by communal religious practice, including screening out free riders through costly signalling or providing ex-post insurance to members of religious groups (Berman [2000], Chen [2010], Iannaccone [1992]). These efficiency-enhancing aspects of religion might be particularly important in settings with weak formal institutions where problems of incomplete information are particularly prevalent. In this paper we focus on such a setting. We examine the interplay between formal market-based insurance and non-formal church-based insurance in Accra, Ghana.

We conduct a lab-in-the field experiment in Accra to test whether insurance is one motive behind religious participation. We do this by randomly assigning free enrollment into a formal, commercially available funeral insurance policy and measuring how this affects willingness to contribute money in a dictator game to the church and two other charitable recipients. The additional recipients - a secular charity and a prayer event - provide a means of differentiating between a club good interpretation of church involvement, where participants care primarily about signalling their behaviour to other church members to benefit from community based insurance, and an interpretation of church participation that encompasses broader spiritual motives, including a form of spiritual insurance directly with God. If people believe that divine powers can influence real outcomes, they may try to act upon this belief by behaving in ways they believe will please God. Such beliefs are important in our religious setting, where people have faith in divine powers that actively intervene in their daily lives as opposed to affecting only a possible afterlife.

We find that enrollment in the formal insurance policy causes church members to give less money to the church in a dictator game. Interestingly, we find that formal insurance also causes church members to give less to the other recipients who are not directly linked to the church, but are associated with church teachings on "good behaviour". We also find that church members simply primed with death risk (they receive information on the death insurance, but not the insurance itself) increase their giving to the church and other charitable recipients.

We set up a model to illustrate the conditions under which we can interpret these results as evidence for insurance. In the model, a church member derives utility from secular and religious consumption. We first show that if religious consumption does not have an insurance motivation, a reduction in perceived losses (through our enrolment treatment) should increase the amount allocated to religious consumption, via an income effect. However, if religious consumption does have an insurance motivation, and if the insurance is perceived as sufficiently effective, the substitution effect of a reduction in perceived losses will outweigh the income effect and lead to a reduction in the amount allocated to religious consumption.

The insurance motive can work either through a reduction in perceived losses from negative shocks because of transfers from other church members, or through a reduction in perceived probabilities of adverse shocks because of belief in divine response to religious giving. Our experiment finds strong evidence for the latter mechanism. Our findings link with some recent studies showing that beliefs in divine intervention in the daily lives of individuals are sometimes an important determinant of real and costly social decisions. For instance, Gershman [2016] and Nunn and de la Sierra [2017] document cases where beliefs in supernatural forces modify individuals' behavior in important ways. In our case, people believe that behaving in ways they believe will please God can significantly reduce their risk of adverse shocks. However, our survey results suggest that churches also provide financial assistance to their members in some cases. We hypothesize that a community-based material insurance exists in parallel.

Finally, we show that exogenous factors that increase religious giving, thereby reducing the

marginal insurance utility from religious consumption, can reduce the probability that the substitution effect outweighs the income effect. Consistently with this, we show that subjects who give substantially more than the average, or who participate in the game during intensive "revival week" events in which churchgoers donate much more than in an average week, demonstrate treatment effects that are of the opposite sign to the average for the sample.

Although our model is an instance of standard micro-economic analysis as applied to the problem of the allocation of resources between secular and religious consumption, our empirical study is methodologically innovative in two main ways. First, we have sought to distinguish carefully between different channels through which religious insurance might work - notably, through influencing the behavior of other members of the religious community as opposed to influencing the probabilities of adverse events themselves that are believed by subjects to be determined only by God. Secondly, we have provided an experimental intervention that directly affects the demand for religious insurance by providing an institutional substitute.

Our findings add to the literature on the economic functions of religious organisations by providing experimental evidence that a religious institution can be used as a substitute for a formal financial service in an environment where obstacles to the functioning of the formal market are high. Furthermore, the experimental findings add nuance to the literature on religious institutions as coordinating platforms by demonstrating that adherents might care as much about spiritual insurance (affecting outcomes through signalling to an interventionist God) as they do about material insurance (accessing transfers of goods and services from other church members).

In the following section, we give an overview of the literature on religion and insurance. In section 3, we present our experimental design. In section 4, we use a simple model to derive our experimental hypotheses to identify an insurance effect and to distinguish between community-based insurance and spiritual insurance. In section 5, we discuss our experimental results and conclude in section 6.

3.2 Religion and insurance

The macro-economic literature, in the wake of Weber [1905], has long recognized the potential importance of culture, and especially religion, for economic growth. However, most empirical studies in this literature suffer from endogeneity problems, and it is generally hard to rule out the possibility that confounding factors explain both the religiosity of a population and the growth of its economy. For instance McCleary and Barro [2006] find in their instrumental variable model that higher GDP per capita causes a reduction in average religiosity, while many studies find the opposite result in OLS regressions (i.e., that higher religiosity leads to lower GDP per capita). Even when it is possible to do so, such large-scale studies have difficulty pinpointing the mechanisms involved. Experimental methods may therefore be helpful both in establishing causality and in identifying the likely mechanisms involved. Our paper precisely aims at understanding a particular economic function of religious organizations: their role as informal insurers.

3.2.1 Risk and religion

There is a broad literature that makes the link between religious participation and risk-coping strategies. In examining religious organisations as insurers, our work closely follows that of Chen [2010], who finds that religious intensity increased with the need for ex-post insurance in Indonesia, and Ager and Ciccone [2016], who find a relationship between higher rainfall risk and religious participation. Religious participation has also been shown to provide partial insurance against fluctuations in consumption and well being (Dehejia, DeLeire, and Luttmer [2007]). Other evidence from cross-country surveys, and historical evidence from the Great Depression demonstrate a degree of substitution between access to social welfare and religious participation (Gruber and Hungerman [2007], Scheve and Stasavage [2006]). We add experimental evidence to this literature, causally demonstrating that access to secular insurance can reduce religious involvement.

3.2.2 Microinsurance

Urban Ghana is a particularly interesting setting in which to study interactions between religious participation and insurance. Relatively low rates of insurance mean that enrollment in a formal

policy is likely to be a meaningful and significant treatment for many of our participants. At the same time, high levels of religious participation allow us to examine any effects of insurance in a setting where religious behaviour is both a salient and commonplace feature of daily life.

In our sample of 576 church members we find that only 30% of all those interviewed participate in the National Health Insurance Scheme, Ghana's public health insurance program. 17% indicate that they hold any other types of insurance. These low rates are consistent with other developing countries where people use a variety of costly strategies to cope with the range of health and financial risks that are not met by formal insurance. In recent years, microinsurance policies have been proposed and tested as poverty alleviation tools with varying degrees of success (Cole, Giné, Tobacman, Topalova, Townsend, and Vickery [2013], Giesbert, Steiner, and Bendig [2011], Giesbert and Steiner [2015], Karlan, Osei, Osei-Akoto, and Udry [2014]). Consistently across studies, take-up has been lower than expected and this has been attributed to a variety of factors including liquidity constraints (Cole et al. [2013]), limited attention (Zwane, Zinman, Van Dusen, Pariente, Null, Miguel, Kremer, Karlan, Hornbeck, Giné, et al. [2011]), trust in the insurance mechanism (Karlan et al. [2014]), and the existence of informal insurance substitutes (Mobarak and Rosenzweig [2013]).

Religious institutions are an important instance of informal networks, especially in Sub-Saharan Africa, yet they have received little attention in the literature. Our experiment explicitly tests how access to a formal insurance scheme impacts the willingness of our subjects to contribute with their offering to church funding and other charities. It contributes to the microinsurance literature by studying in a controlled environment how religious participation might affect demand for formal insurance. Our results strongly suggest that formal and spiritual insurance are substitutes for each other, though we would not wish to claim that insurance is the only or even the main motivation for religious adherence and participation.

3.2.3 Pentecostalism

The importance of religious institutions in Africa is well represented by the startling increase in the popularity and influence of Pentecostal churches across much of the continent. Pentecostalism and

related Charismatic movements represent one of the fastest-growing segments of global Christianity. Approximately a quarter of the world's two billion Christians are members of these churches (Pew Research Center [2006]). A large share of them are found in Sub-Saharan Africa, where 28.3% of the population belongs to a Pentecostal or Charismatic movement according to the 2010 census (Pew Research Center [2011]).

Participants in our experiment were recruited from different branches of the Assemblies of God church, one of the oldest Pentecostal denominations in Ghana (and also across much of sub-Saharan Africa). The church has approximately six thousand congregations and two million adherents in Ghana.[1] The doctrines of the church are broadly similar to those expressed in other Pentecostal churches in Ghana, and indeed Assemblies of God was one of the founding churches of the Ghanaian Pentecostal and Charismatic Council (GPCC), an umbrella association of Christian church denominations that are united by a set of Pentecostal doctrines.

Pentecostalism and Charismatic movements emphasize the work of the Holy Spirit and claim that spiritual gifts, such as prophecy, divine healing and speaking in tongues are expected to be present in the lives of believers (Pew Research Center [2006]). Although in theory Pentecostal and Charismatic movements differ on some aspects, these aspects are marginal for our study, and we will use the term Pentecostal broadly. This makes sense especially in Ghana, where the popular speech hardly draws a distinct line between Pentecostalism and Charismatism (Okyerefo [2011]).

For adherents of Pentecostal movements, the church is an essential part of their life. They go to church regularly, more than other Christians (Pew Research Center [2006]). They also perform their religious practices more frequently. For example, compared to the general population, Pentecostals pray and read the Bible more often, and more frequently watch or listen to religious programs on television and radio. They are also more likely to share their beliefs with others to spread their faith (Pew Research Center [2006]).

Members also enjoy non-spiritual benefits from their church. An essential function of Pente-

[1] World Christian Database. http://www.worldchristiandatabase.org/wcd/about/religions.asp

costal churches in Ghana, in particular in urban areas, is to offer a place for social gathering. For instance, 41% of study participants declare that they have found their spouse (or are most likely to find their future spouse if not already married) in church. Some church members even report that they favour church members as business partners (48% of church members in our study). More fundamentally, people seem to be attracted to such churches because they feel part of a broader community which looks after them, be it through other church members, church leaders, or God. For example when faced with any personal or family problems, 69% of our participants would call their pastor and 25% would ask another church member for help.

Table 3.1 presents some descriptive statistics of the six church branches where we recruited participants for our study. We approached these churches using a snowball sampling strategy. The church branches are heterogeneous in terms of age, size, members' characteristics, and geographical locations in the city. They represent the great diversity of Pentecostal churches that can be found in Accra. The teachings and organizational structures of these churches are mirrored across much of sub-Saharan Africa where Assemblies of God claims sixteen million adherents and together, Pentecostal churches account for almost 40% of all African Christians. In the next section, we discuss the particular set of Pentecostal teachings that are captured by the model of insurance we propose.

While many of these teachings are fairly standard across African Pentecostal churches, we do not believe that the lab-in-the field set up of our experiment attracted a fully representative sample of church-goers. Indeed Table 3.3 shows that our subject pool differs from the Ghanaian national averages in ways we might expect given that experiments were conducted during the working week. We attracted participants who were less likely to be employed, earned less on average, and were younger than the Ghanaian average. These characteristics could interact with perceptions of insurance. In our results however, we present our treatment effects with controls showing that the insurance effects are robust to variations along these dimensions within our recruited sample.

3.2.4 Pentecostalism and insurance

Perceived links between insurance and the church could be particularly strong in Pentecostal churches in urban Africa. Some reasons for this are general to religious communities across the world. For example, the costs of religious participation can be seen as screening mechanisms to ensure that members are reliable and to prevent free-riding (Iannaccone [1992]). Additionally, the community structure of the group with repeated interactions reduces monitoring costs (Berman [2000]). Furthermore, the heterogeneity of church members means that shocks are likely to be relatively independent and risk preferences are likely to be heterogeneous, implying that churches might be well placed to provide insurance within their networks (compared, say, to workplaces). Particularly important in the African context is the fact that previous work has shown the effectiveness of insurance interventions to depend crucially on trust in the insurance provider (Cole et al. [2013], Karlan et al. [2014]). Survey evidence from the Afrobarometer and the World Values Survey shows that across Africa, religious leaders are considered amongst the most trustworthy members of civil society. They are expected to take responsibility for their members' welfare in the absence of government-led social interventions and these expectations are enhanced by urbanization (McCauley [2013]).

This setting where ideas about religion and insurance are closely linked is ideal for a controlled experiment for one additional reason. The teachings of Pentecostal churches make participation costs explicit. Church members are expected to make large and frequent financial contributions to the church and other spiritual goals as part of their religious participation (Gifford [2004]). Thus we can examine financial contributions to the church and religious goods as an outcome variable that is directly linked to church membership and involvement.

These financial contributions are layered and the different ways of transferring money might have different motivations. *Tithing*, the practice of giving away a tenth of all income, usually takes the form of a non-anonymous monthly payment to the church for which church members receive a receipt. This type of giving is akin to a membership fee to the church community. On the other hand, *pledges to the church* are occasional non-anonymous donations involving large amounts of money, often for a specific purpose such as purchasing a bus or founding a new church branch.

Finally, there are *spontaneous offerings*, made on a more regular basis, which are generally anonymous and the amounts given unobserved. This includes among others *seed offerings* - the practice of giving money in anticipation of a future material benefit, or *thanksgivings* in gratitude for already materialized benefits (Maxwell [1998], Gifford [2004]). The type of giving we observe in our experiment falls into this category of spontaneous giving.

Giving to the church might interact with the use of the church as an insurer in a number of ways. Firstly, individuals might give to the church in expectation that the church as an institution would reward this sign of commitment by disbursing funds in times of need. Secondly, individuals might use their public giving to send signals that they are good community members to other church members, and expect that other church members then contribute to help them in times of need. These two types of community-based insurance could be considered "material" insurance. Finally, in addition to its role as a social network, the church is also a setting for encounters with the divine. This role is important in settings such as Ghana, where there are strong beliefs in a divine power who influences daily lives (World Values Survey, Gifford [2004]). In this case, the church might have value as an insurer because it facilitates access to a divine power who is believed to intervene to prevent negative shocks, and giving to religious goals is seen as fulfilling a Christian duty that will be rewarded by this God. We call this type of insurance "spiritual" insurance. We try to incorporate a test for this into the design of the experiment by allowing participants to give both directly to the church, but also to other causes that are separate from the church, but could still be seen as fulfilling the spiritual duty of giving.

3.3 Experiment

We ran an experiment in Accra, Ghana that randomly enrolled church members in a funeral insurance policy offered by a leading micro-insurer active in the Ghanaian market. The outcomes we measured were allocations out of an endowment towards a participant's church and two other non-church recipients.

3.3.1 Enrolment treatment: Funeral insurance policy

Funerals are large and costly events in many sub-Saharan African societies (Berg [2016], Case, Garrib, Menendez, and Olgiati [2013]). Surviving family members are often expected to honor the dead through lavish commemorations. The rising toll of funeral costs has received attention from academics and political leaders, and more recently private financial service providers have begun to offer savings and insurance products designed specifically to meet these costs.

In Ghana, guests and other members of the bereaved's community typically make contributions that help to cover the funeral costs. It is important to note that community support is not only financial - churches also organise provision of food and moral and logistical support, so any formal insurance product will only be addressing a single aspect of the church contributions. The degree of formalisation of this type of support varies across the churches in our sample. In interviews with church leaders, most confirmed that observed commitment from members was a prerequisite for church involvement in their funerals. Definitions of commitment always included attendance of church events and financial commitment to the church in terms of tithes and offerings.

The funeral policy we offered to participants covered the life of the participant and a member of his or her immediate family. If either of these parties were to pass away within a year, the policy would pay GHS 1000 ($265) to the surviving family members. This policy cost GHS 12.5 ($3USD) per family per year. Individuals in this treatment were enrolled on the spot after completing a demographic survey. In our main sample, among the individuals randomized in the insurance group, only three participants (approx. 2%) did not receive insurance.[2]

In order to verify the extent to which the treatment was meaningful for insured participants, we conducted a follow-up survey in March 2017.[3] Of the 576 participants in our experiment, we were able to obtain phone numbers for 407 (71%), and of these we were able to obtain responses with usable data from 182, representing 32% of our total experimental sample. Of these 63 had been enrolled in the insurance treatment, and 53 of these (84%) correctly recalled this fact (of the

[2]These individuals could not be enrolled in the insurance policy because they were already enrolled in a similar funeral insurance scheme or because they refused to sign up.

[3]Full details of this follow-up survey are available from the authors on request.

remainder, 5 recalled incorrectly that they were not enrolled, while 5 could not remember). Given that around two years had elapsed since the experiment, and that the enrolment was for a period of one year, we consider that a correct recollection rate of 84% is broadly encouraging. None of the insured individuals had experienced a bereavement that would have entitled them to an insurance payment, so we were not able to verify how effectively the mechanism had functioned.

3.3.2 Priming treatment: Providing insurance information

It became clear during pre-tests that discussions of death and planning around death would be very sensitive topics. Reluctance to contemplate large unpleasant risks has been raised in the literature, particularly in other developing country settings where people are severely limited in the steps they can take to address these risks (Case et al. [2013]). Furthermore, findings in psychological research show that awareness of mortality can modify religiosity and beliefs in a supernatural entity (see for instance Jong, Halberstadt, and Bluemke [2012], Norenzayan and Hansen [2006]). Willing participants in the insurance treatment were directly enrolled in the policy at the start of the experiment, so the treatment necessitated a lengthly discussion about planning for death.

As the experiment was designed to isolate the effect of being *enrolled* in insurance, we offered the same information about the insurance policy to the control group, so that the same issues of death would be salient in both settings. To isolate the potential effect of risk priming, we had a second treatment where people were not informed about the content of the insurance policy. Comparisons between this group who did not discuss death and the control group who received insurance information allow us to verify that there was indeed a priming effect.

Our follow-up survey revealed a higher treatment recall error in this priming treatment group than in the insurance treatment group. Of the individuals contacted who were able to provide usable data, 57 had received the priming treatment and of these only 18 (32%) correctly recalled that they had not been provided with insurance, only with the information about insurance. Nevertheless, at around two years after the event it is unsurprising that a greater proportion of those who were not insured should be in error than of those who were insured.

This and other experimental details are documented in the pre-experiment registration submitted to the AEA registry.[4]

3.3.3 Recruitment

We recruited 576 study participants from different church branches within one particular denomination. Participants for the main study were recruited from six church branches through announcements made on Sunday mornings during regular church services, and to avoid confounds with normal Sunday offering, all sessions took place during the subsequent work week. A subset of participants were inadvertently recruited during "revival weeks" when their churches were engaged in active fundraising services during the work week. We found interesting results for this subset, which are discussed after presenting the main experimental results.

It was very important to the credibility of our study that the study take place off church premises and that participants be assured of anonymity so as to avoid any contamination of the results by perceived pressure from the church authorities. This involved a substantial effort to transport the recruited individuals to a study location at some distance from the church, as well as the setting up of a proper lab-in the-field with physical division between subjects so as to make the assurance of anonymity credible.

We were also interested in seeing how our hypothesised mechanisms operate within a secular organisation, so we recruited an additional 242 market sellers. Traders in this market are organized into an association that could provide financial assistance such as credit or insurance to dues-paying members. During the first round of data collection, we realized that the insurance treatment did not operate in this sample as it did within the group of church members. Indeed, the funeral insurance was coordinated by the head of the market association and informal discussions with study participants cautioned us that trust in the insurance coordinator might be low. Furthermore, questionnaire answers informed us that the market association is not a commonly-used risk sharing structure, and is by no means similar to the church community in that respect. We therefore

[4] AEA RCT Registry ID: AEARCTR-0000558

stopped collecting data on market members after the first round of the study and the sample for this group is too small to be able to detect treatment effects. Results from this smaller additional sample are available from the authors on request.

3.3.4 Experimental Setup and Design

Interested participants were assigned to sessions of 8 - 12 people. With the exception of recruitment, all interactions with participants took place off the church premises in a neutral location set up with laptops and room dividers where participants could answer survey questions and privately complete their decisions in the dictator games. All participants were compensated for transport to the neutral locations.

A session consisted of an extended survey and a set of dictator game decisions. These decisions are described further below. Each participant was interviewed by an enumerator who spoke the participant's local language.

Participants played 10 modified dictator games. Each game asked participants to allocate GHS 11 (a little less than average daily income) between two recipients. The set of recipients consisted of the participant's church, a secular charity, a national prayer organisation, and the possibility of keeping the money. There were also two ways in which individuals would give to the church: the first being an anonymous donation, the second being a named donation. The pairs of recipients are listed in Table 3.2.

The Street Children's Fund is a charity that takes care of the education needs of homeless and vulnerable children. The charity operates in a district of the city that is geographically and culturally distinct from the ones where we recruited participants. Giving to this charity could largely be understood as an altruistic action. The thanksgiving offering is part of an annual inter-faith prayer event. Leaders and members of various faiths join together in prayer for Ghana. Giving towards this event was meant to be interpreted as giving towards a largely spiritual interest. Pre-tests and focus groups during piloting confirmed that study participants would see these two recipients in

this manner.

Participants were paid a flat show-up fee of GHS 20. After all decisions had been made in the dictator games, one game was selected at random, and further payments were made according to the decision taken for that game. This meant that participants had the opportunity to earn up to GHS 31. Average overall earnings from the experiment were GHS 22.50.

3.4 Model

We develop a simple model to formalize the types of behaviour we expect our experiment to capture, and use results from the model to motivate the experimental hypotheses.

First we establish how church members who derive utility from secular as well as spiritual consumption would behave after provision of insurance if there is no insurance offered by the church. We then consider two insurance channels. Community-based insurance is modelled as a payment given to a church member in the case of a loss where the size of the payment depends on how much the church member gives to his own church. Spiritual insurance is modelled as a belief that the subjective probability of a loss is reduced by giving to the church and other goods used for religious signalling, such as the spiritual and secular charities. Under the insurance treatment, the provision of insurance reduces the size of a potential loss. We capture the priming effect of insurance information as leading to a perceived increase in the size of a potential loss. The extensions to the baseline model of no insurance show how in the presence of an insurance motive in the church, the main insurance treatment can lead to a decrease in giving, and the provision of only insurance information can lead to an increase in giving.

3.4.1 Setup

We assume that a church member has an income of Y and chooses to give an amount g to the church. The church member enjoys utility $u(Y - g)$ from consuming $Y - g \geq 0$ secular goods, and

utility $\theta f(g)$ from contributing $g \geq 0$ to church goods. The parameter θ reflects the relative weight the individual puts on church activities compared to secular consumption. This weight might differ from one individual to the next (i.e., individual heterogeneity). More importantly for our empirical analysis it might also differ in time (i.e., in revival weeks individuals go to church everyday and are focused on spiritual activities). Thus a church member who gives g to the church enjoys a total utility of $u(Y - g) + \theta f(g)$. Both utility functions are increasing and concave in their arguments. In each period, church members face a probability π of an income loss of size D.

Under the assumption that insurance is offered through the church, giving also has the impact of reducing the size of the loss, thus the total loss would be $D - l(g)$. Under the assumption that church members believe in spiritual insurance, the probability of a loss is decomposed into a basic probability of loss $\tilde{\pi}$, and a reduction in the probability of loss that can be mitigated by giving money to spiritual goods. Therefore, the total subjective probability of loss is $\pi = \tilde{\pi} - p(g)$.

The following subsections set-up the maximization problems and show how optimal giving varies with the perceived size of loss. All proofs are in the appendix.

3.4.2 Optimal giving to the church in the absence of any insurance

In this section we assume that church members choose a particular level of giving g to maximize their total expected utility. There is no insurance offered through the church.

$$\max_{g} \quad (1 - \pi)u(Y - g) + \pi u(Y - g - D) + \theta f(g) \tag{3.1}$$

Solving for the first order conditions and taking optimal giving g^* as a function of D allows us to show that giving is decreasing with the size of the loss D:

$$\frac{\partial g^*}{\partial D} < 0 \tag{3.2}$$

This classical result of consumption smoothing comes from the standard concavity assumptions of the utilities derived from secular and religious consumption. When faced with an increase in the

potential loss D, church members shift spending from religious consumption to secular consumption to ensure a higher level of secular consumption in case of loss. We call this result the "income effect".

Therefore, this subsection predicts that if there is no insurance mechanism in the church (neither community-based, nor spiritual), the information treatment, by increasing the perceived loss D, would lead individuals to decrease church giving g^*. Compared to the information treatment, the enrolment treatment decreases D, and thus would increase giving to the church.

3.4.3 Community insurance: optimal giving when giving reduces the size of a loss

In this section we assume that the church community provides material insurance such that church giving reduces the size of the loss, $L = D - l(g)$. In this case, church giving can be seen as payment of the premium of an informal insurance that covers part of the possible loss. As it is offered by the church community, only giving to the church - and not giving to other religious goods - provides access to this type of insurance. The utility maximization problem is as follows:

$$\max_{g} \quad (1-\pi)u(Y-g) + \pi u(Y-g-D+l(g)) + \theta f(g) \tag{3.3}$$

We solve for the first order conditions and express optimal giving g^* as a function of the loss D. We find that:

$$\frac{\partial g^*}{\partial D} > 0 \Leftrightarrow l'(g^*) > 1 \tag{3.4}$$

When there is an insurance motive behind church donations, an increase in the potential loss D triggers two opposite effects: the substitution effect, whereby church members try to mitigate the increase in loss by buying more informal insurance; and the income effect' described in the section 3.4.2 where church members reduce giving to the church to have more money available for secular consumption smoothing.

Condition (3.4) shows that as long as community-based insurance is effective enough in decreasing the loss, which is the case for low enough g^*, the consumption-smoothing effect from the

baseline model (income effect) is outweighed by the increased demand for church insurance (substitution effect). Therefore, the overall effect of an increase in D is an increase in the optimal giving.

This subsection therefore predicts that if there exists an effective community insurance that reduces the size of a loss in case of a shock, the information about insurance should increase church giving (compared to no treatment) while the enrolment treatment would decrease church giving (compared to the information treatment). There should be no impact of either treatments on giving to other recipients.

3.4.4 Spiritual insurance: optimal giving when giving reduces the subjective probability of a loss

In this section we assume that there is a spiritual insurance motive such that giving reduces the subjective probability of the loss $\pi = \tilde{\pi} - p(g)$. It is important to stress that giving can be to the church or to any other charitable/spiritual organizations that can be used for religious signalling. The mechanism here works through God: being a good Christian reduces the subjective probability of a negative shock. Utility can now be written as:

$$\max_{g} \quad (1 - \tilde{\pi} + p(g))u(Y - g) + (\tilde{\pi} - p(g))u(Y - g - D) + \theta f(g) \tag{3.5}$$

We can show that:

$$\frac{\partial g^*}{\partial D} > 0 \Leftrightarrow p'(g^*)u'(Y - g * -D) > (\tilde{\pi} - p(g^*))u''(Y - g^* - D) \tag{3.6}$$

This condition is harder to interpret intuitively in the non-parametrized form, so we defer the discussion to the appendix where we investigate it using a CARA utility function. In short, we find that the optimal giving g^* is increasing in the size of loss D when the spiritual insurance is effective enough. Indeed, when this is the case, individuals prefer to invest in decreasing the subjective probability of loss by increasing their religious giving (substitution effect) rather than smoothing consumption (income effect).

Therefore, this subsection predicts that providing participants with insurance information would increase giving to any charitable or spiritual organization (compared to no treatment) while enrolling them in the insurance treatment would decrease giving to any charitable or spiritual organization (compared to the information treatment).

3.4.5 Experimental hypotheses

This subsection derives experimental hypotheses from the model's predictions and explains how the experiment can help us distinguish between these different hypotheses.

H0 There is no insurance provided through the church (section 4.2).

- **H0a** Compared to no treatment, insurance information decreases giving to the church (or has no effect).
- **H0b** Compared to information treatment, insurance enrollment increases giving to the church (or has no effect).

H1 *Community* insurance is provided through the church (section 4.3).

- **H1a** Compared to no treatment, insurance information increases giving to the church.
- **H1b** Compared to information treatment, insurance enrollment decreases giving to the church.
- **H1c** There should be no effect on giving to outcomes that do not affect the size of the loss. Thus, there should be no effect on giving to the thanksgiving offering or the street children's fund.

H2 *Spiritual* insurance is provided through the church (section 4.4).

- **H2a** Compared to no treatment, insurance information increases giving to the church.
- **H2b** Compared to information treatment, insurance enrollment decreases giving to the church.
- **H2c** Giving to other recipients that might affect the subjective probability of loss should be affected. Thus, there should be similar effects to giving to the thanksgiving offering or the street children's fund as the effects on giving to the church.

Thanks to our experimental design, we can test for an insurance mechanism in giving (test for H0a against H1a/H2a and H0b against H1b/H2b) and then test the two insurance channels of spiritual and community-based insurance against each other (H1c against H2c).

3.5 Experimental results

3.5.1 Descriptive statistics

Our main results include 454 church members recruited during regular service weeks from six different church branches. Table 3.3 summarises the basic demographics of these participants. The final column in this table also includes nationally representative demographic information. Consistent with the recruitment process taking place in churches that are not gender-balanced, we find that our study population had more women than men. Only a fifth of our participants had completed at least a high school education, and 45% held any sort of insurance prior to participating in the study (including the National Health Insurance). On average, our participants earned approximately GHS 350 per month or roughly GHS 12 per day, equivalent to $92 dollars per month, or a little more than $3 per day. The groups were balanced across treatments for all key variables, as shown in Table 3.4. An F-test rejects the hypothesis that these main demographic variables jointly explain assignment to any of the treatments. Compared to the national population, our participants had lower incomes, were less likely to be employed, and attended church more frequently.

The demographic variables discussed above come from the survey conducted prior to the dictator game decisions. The survey also covered questions on the relationship between participants and the church. We find that the church is important to members as a financial institution, but this aspect of the relationship is not the only motivation. The most popular reason given for going to church is that, "the teaching of God corresponds to what I believe in" (53% of participants). Yet 24% of participants have also received financial support from the church within the last two years, and whereas only 16% of participants would go to a a bank or any other type of financial institution for help, 25% of them would go to their church for financial assistance. Thus, self-reported survey measures demonstrate that there is a financial role for the church. We turn next to the experimental

results which test whether and how insurance might be part of this role.

3.5.2 Summary of the allocation decisions

Participants played a series of dictator games and in each dictator game they were paired with one of three recipients - an anonymous donation to the participant's own church, the street children's fund, or the thanksgiving offering. In each game, participants decided how much to keep for themselves out of an endowment of GHS 11, equivalent to their daily income, and how much to give to the recipient.

The histograms in Figure 3.1 plot the distributions of giving to the three different recipients. On average, participants chose to keep 5.77 GHS or 52% of their endowment, and give 5.22 GHS or 48% of the endowment. There was some concern that participants would avoid making a decision by focusing on the median allocation. We find that 40% of participants selected an allocation of either 5 GHS or 6 GHS. Across recipients, roughly 7% of participants gave nothing, and 10% of participants gave everything away. These spikes at the extreme values highlight that allocations to the recipients may have been censored. To account for this, we report all experimental results using a Tobit regression.

We also find that giving towards the three recipients is significantly correlated, with the correlation coefficients between the pairs of choices ranging from 0.52 to 0.59. If the experimental design induced any order effects, these high degrees of correlation could be problematic for interpretations across recipients. However, the order of dictator decisions was randomised across participants, mitigating the concern that any order effects could interact with treatment effects.

3.5.3 Treatment effects

The effect of only insurance information

The first treatment effect tests the hypothesis that a more salient threat of death and a discussion of the associated risk coping strategies affects giving. Table 3.5 presents the basic results of the

insurance information treatment on giving relative to the no information setting. In the sessions with no additional information, participants gave an average of GHS 5.05, or 45% of the endowment to the church. Participants who received insurance information increased giving by GHS 0.78 or 7% of the endowment. This increase in giving is consistent with the hypothesis that the focused discussion of risk puts participants in a fearful state, which makes them more likely to give money to the church. There was also an increase in giving of similar magnitude to the street children's fund (an increase of GHS 1.00) and the thanksgiving offering (an increase of GHS 0.75).

The effect of being enrolled in an insurance policy

Table 3.6 presents the results of the effect of actually being enrolled in an insurance policy. These results are obtained by comparing people who received insurance with people receiving only insurance information. Column 1 demonstrates that enrolment in the formal insurance policy reduces giving to the church by GHS 0.92. Again, we find similar effects regarding giving to the street children's fund and giving to the thanksgiving offering.

These effects are robust when we control for a large set of church and demographic characteristics as demonstrated in the Appendix, Tables 3.9 and 3.10. In these tables, the effect of priming on death and the insurance effect are combined by taking the total experimental population and using insurance information as the reference treatment. The coefficient on no insurance reflects the priming effect while the coefficient on insurance reflects the insurance effect. Table 3.9 includes measures for individual religiosity while Table 3.10 includes dummy variables for each church branch. These controls should pick up variation in church structure on important characteristics such as the level of formal church support during members' funerals and any variation in church teaching on giving. Neither the individual level characteristics nor the church characteristics explain the treatment effects on giving.

3.5.4 Discussion

How does insurance work in the minds of church members?

These experimental results point to an interesting relationship between the types of insurance church members might believe they receive from the church, and their willingness to engage in costly behaviours to signal membership of the church. Firstly, treatment effects are present across the three recipients. As discussed in earlier sections, neither the street children's fund nor the national thanksgiving offering are linked to the participant's church. If the type of insurance the participant associates with his church membership is purely community based, there should not be a treatment effect on giving to these external recipients. As decisions were made privately and off the church premises in the middle of the working week, it is very unlikely that giving to these charities was used as a means of signalling good behaviour to other church members or church leadership. Thus, the fact that we find effects of giving to these non-church recipients in addition to giving to the church indicates that part of the insurance channel works through beliefs that encourage giving as an act of worship to a divine god.

To investigate this spiritual insurance mechanism, we look at the treatment effects in other dictator games played by participants (as described in Table 3.2). First, we investigate the possibility to give to the church where the participant's name would be attached to his donation rather than an anonymous giving. Table 3.11 in the Appendix shows that the priming and enrolment treatments have the same effect on church giving when donations are not anonymous as when they are.

The fact that our subjects do not try to signal their generosity through the use of nominal donation motivates the interpretation that charitable behaviour is used as a spiritual psychological mechanism to cope with risk.

We also show in the Appendix that both the priming treatment and the insurance treatment do not modify participants' decisions to allocate money to their own church against charitable recipients (Table 3.12, columns 1 and 2) nor the money allocation between the two NGOs (Table 3.12, column 3). It seems that the three different beneficiaries are equally important in the participants'

mind for coping with risk.

The GHS 11 endowment used in the dictator games is a little bit more than the median weekly offering to the church. Comparing giving in the insurance information treatment with the no insurance treatment, it is interesting to see that a relatively brief discussion about death could raise giving by 6.5%, and provides an indication of the importance of the church in this context where there is a lot of uncertainty, but few institutions to deal with it.

One final result of interest is that in our follow-up survey, 15% of those in the insurance treatment and 29% of those in the insurance priming treatment reported having purchased insurance themselves since the experiment. Furthermore, 89% of the former and fully 95% of the latter reported that they would be interested in purchasing funeral insurance in the future. While far from conclusive, these findings suggest that exposure to information about formal sector insurance can significantly affect subjects' attitudes to purchasing insurance, in ways that imply the churches may under some circumstances be a facilitating mechanism rather than an obstacle to the growth of the formal sector.

Heterogeneous treatment effects: church members during fund-raising events

Up to this point, we have discussed results for church members recruited during normal service weeks. After recruitment, we learnt that two churches had hosted revival weeks during the course of our experiments. Revival weeks are special periods of church activity where members are encouraged to attend church daily. The services consist of prayer, teaching, singing, and exhortation to give money to the church.

Asamoah-Gyadu [2015] describes revival meetings as an essential feature of contemporary Pentecostal liturgy. In his view, Pentecostal teaching is focused on "scriptures applied in ways that encourage members to invest in financial markets, seize oppotunities in education, business, politics and entertainment and wherever able, increase their spheres of influence in the world". Access to these material benefits is accomplished through religious activities including "massive revival

meetings, summits and conferences, all day prayer services and all-night prophetic vigils and mass evangelistic crusades".

In total, 119 church members participated in the experiment while they were in the middle of a revival week. In terms of demographics, we don't find them to be different from members recruited during regular service weeks (see Table 3.7). However, we find important differences in treatment effects. After receiving insurance information, revival week members *decreased* giving to the church and after being enrolled in insurance, they *increased* giving to the church (see Table 3.8). For comparison the analyses of other donations are in the Appendix.

Referring back to the model, these results are consistent with interpreting the revival week as an upwards shift of θ, the relative weight in our subjects' utility function of church activities compared to secular ones. During revival weeks the importance of the church in our subjects spiritual life is magnified, which in term of the model means that there is an upward shift of θ. As equation (3.36) in the Appendix demonstrates, when equilibrium giving is higher than a given threshold, even in the presence of spiritual insurance, church members respond to an exogenous shock decreasing the size of a loss by a decrease in optimal giving. Intuitively, there is a point at which members have already given so much money to the church, that when faced with the prospect of a negative income shock, they prefer to keep money to smooth secular consumption (i.e., when g^* is large, the income effect dominates the substitution effect).

This explanation of the revival week effect is consistent with the types of activities and benefits members are supposed to derive from revival weeks. Additionally, we find suggestive evidence that people who self report to be habitually high givers respond to treatment in the same manner as people who completed the experiment during a revival week (see Tables 3.15 and 3.16 in the Appendix). In other words, their reaction to our treatments is the reverse of the reaction of people who are not in revival week, confirming that for high givers the income effect dominates the substitution effect.

3.6 Conclusion

We conducted a lab-in-the-field experiment with church members from an established Pentecostal church in Accra, Ghana. We find evidence for religious and charitable giving being part of a church member's risk-coping strategy. This spiritual insurance channel does not contradict the possibility that other church community-based mechanisms exist in parallel. Indeed, survey responses from church members and leaders emphasize the important roles the church plays as a financial contributor.

The homogeneous treatment effects obtained within the church population depend on three important factors. First, Pentecostal churches stress the involvement of God in terms of blessings in everyday life and teach about God rewarding religious and charitable giving. This particular religious discourse makes members of these churches more prone to see charitable behaviour as a means to decrease the risk of bad events happening and to increase the occurrence of good events. Second, trust in the insurance is fundamental, especially in a context where formal institutions are generally weak. In our case, the church was used as a coordinator for the insurance scheme and participants seemed to trust the insurance because it was coordinated by the church. Finally, our results obviously depend on the absence (or limited presence) of better institutions to deal with risk.

We believe that our results would hold in other Pentecostal churches and settings where the development of formal insurance is low. Since the focus on beliefs in religious rituals that influence immediate events are common among a variety of religions and faiths, it would be interesting to reproduce the experiment in a different religious setting.

The experiment stressed the importance of religion for economic decisions made by individuals in a setting with weak formal institutions. While individuals might go to religious institutions in those settings because they offer risk-mitigating strategies, we show that formal, private insurance can at least partially substitute spiritual based insurance mechanisms. Since the church was used as a coordinator for the insurance scheme, we are inclined to see religious institutions in this context as opportunities to spread formal insurance rather than as an obstacle, a conclusion underlined by

the results of our follow-up study reported above.

3.7 Tables and figures

Table 3.1: Summary statistics of church branches

	(1) mean
Age	26.17
Number of church members (approx.)	1035.67
Church members have an education level higher than average	0.33
Church members have income higher than average	0.17
Average number attending Sunday service	610.00
Average amount received on a Sunday	1150.00
The church owns its building	0.83
The church owns other properties	0.17
Number of paid staff	6.67
The church has a welfare fund	1.00
Observations	6

Table 3.2: Pairs of dictator game recipients.

A	Self	Church (anonymous)
B	Self	Street children
C	Self	Thanksgiving
D	Self	Church (non-anonymous)
E	Church (anonymous)	Street children
F	Church (anonymous)	Thanksgiving
G	Church (anonymous)	Church (non-anonymous)
H	Street children	Thanksgiving
I	Street children	Church (non-anonymous)
J	Thanksgiving	Church (non-anonymous)

Table 3.3: Summary statistics of study participants and comparison with general population

	(1) Study participants mean	(2) General population mean
female	0.61	0.52
married	0.39	0.39
higher education	0.26	0.15
employed	0.56	0.76
income	359.39	445.50

Note: Figures for general population are from Ghana Living Standard Survey Round 6.

Table 3.4: Treatment balance

	(1) Insurance mean	(2) Insurance information mean	(3) No insurance mean
female	0.54	0.63	0.67
age	36.66	35.43	36.04
married	0.40	0.39	0.38
higher education	0.26	0.23	0.27
employed	0.55	0.53	0.60
monthly income	375.44	358.04	345.13
going to church daily	0.07	0.06	0.07
frequent prayer	0.81	0.85	0.80
any insurance	0.39	0.41	0.38
Observations	165	120	169
F stat		.52	.8
p-value		.86	.62

Figure 3.1: Distribution of giving among normal church population.

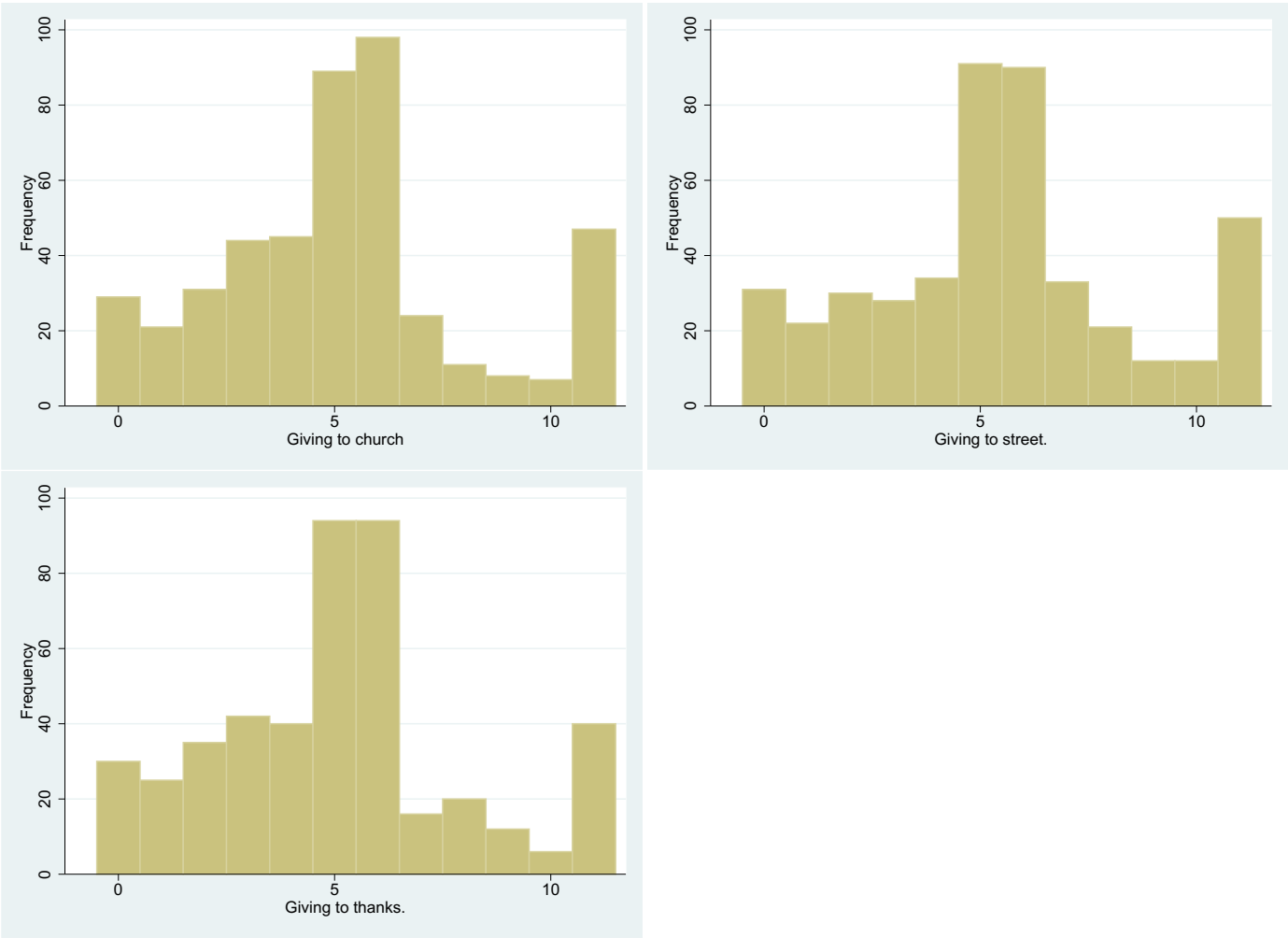


Table 3.5: Giving after receiving insurance information compared to giving with no insurance nor insurance information

	(1) Giving to church	(2) Giving to thanks.	(3) Giving to street.
model			
Insurance information	0.778*	0.746*	1.004**
	(0.450)	(0.448)	(0.457)
Constant	5.045***	4.937***	5.220***
	(0.256)	(0.204)	(0.266)
Observations	289	289	289

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.6: Giving after enrolment in insurance compared to giving with insurance information only

	(1) Giving to church	(2) Giving to thanks.	(3) Giving to street.
model			
Insurance	-0.915*	-0.930*	-0.926**
	(0.471)	(0.502)	(0.434)
Constant	5.846***	5.703***	6.227***
	(0.385)	(0.408)	(0.377)
Observations	285	285	285

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.7: Comparison of regular and revival week participants

	(1) Non revival participants mean	(2) Revival participants mean
female	0.61	0.60
age	36.10	34.63
married	0.39	0.30
higher education	0.26	0.35
employed	0.56	0.55
monthly income	359.39	358.17
going to church daily	0.07	0.11
frequent prayer	0.81	0.95
any insurance	0.39	0.49
Observations	454	122
F stat		1.61
p-value		.11

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 3.8: Treatment effects on church giving for total sample (column 1) and revival week only (colmun 2)

	(1) Giving to church	(2) Giving to church
model		
Insurance	-0.911*	2.249***
	(0.475)	(0.661)
No insurance	-0.878*	2.033**
	(0.460)	(0.956)
Revival week	-2.247***	
	(0.619)	
Revival week X Insurance	3.065***	
	(0.824)	
Revival week X No insurance	2.866***	
	(1.062)	
female	0.0816	0.602
	(0.346)	(0.689)
age	0.0170	0.0624**
	(0.0148)	(0.0281)
log(income)	0.00164	-0.496
	(0.172)	(0.358)
higher education	0.490	1.032
	(0.408)	(0.761)
employed	0.424	1.044
	(0.326)	(0.733)
Ewe	0.137	-0.125
	(0.399)	(0.745)
Ga	-0.334	1.190
	(0.418)	(1.026)
other ethnicity	0.887**	1.451*
	(0.451)	(0.840)
Constant	4.726***	2.468
	(0.956)	(1.877)
Observations	521	117

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

3.8 Appendix

3.8.1 Additional Tables

Table 3.9: Giving with controls for church involvement

	(1) Giving to church	(2) Giving to thanks.	(3) Giving to street.
model			
Insurance	-0.904*	-1.059**	-1.068**
	(0.485)	(0.536)	(0.450)
No insurance	-0.848*	-0.920*	-1.182**
	(0.459)	(0.477)	(0.480)
female	0.0106	-0.420	-0.725
	(0.404)	(0.361)	(0.492)
age	0.00629	-0.0100	0.00312
	(0.0160)	(0.0146)	(0.0159)
higher education	0.259	-0.121	-0.552
	(0.471)	(0.421)	(0.418)
log(income)	0.158	-0.120	0.296
	(0.206)	(0.243)	(0.210)
employed	0.221	0.588	0.0740
	(0.367)	(0.425)	(0.413)
Ewe	0.137	-0.208	0.378
	(0.456)	(0.470)	(0.462)
Ga	-0.673	0.00685	0.0929
	(0.410)	(0.420)	(0.544)
other ethnicity	0.707	0.797*	0.402
	(0.530)	(0.446)	(0.476)
frequent prayer	-0.146	0.620	-0.691
	(0.507)	(0.567)	(0.599)
going to church daily	0.206	-0.179	-0.226
	(0.480)	(0.584)	(0.589)
Constant	4.678***	6.149***	5.733***
	(1.185)	(1.287)	(1.317)
Observations	404	404	404

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.10: Giving with controls for the church

	(1) Giving to church	(2) Giving to thanks.	(3) Giving to street.
model			
Insurance	-0.762*	-0.977**	-0.968**
	(0.430)	(0.489)	(0.445)
No insurance	-0.703	-0.875*	-0.998**
	(0.451)	(0.456)	(0.467)
female	0.00841	-0.368	-0.790
	(0.402)	(0.348)	(0.486)
age	0.00264	-0.0130	-0.00105
	(0.0161)	(0.0141)	(0.0152)
higher education	0.272	-0.151	-0.478
	(0.462)	(0.421)	(0.429)
log(income)	0.110	-0.125	0.219
	(0.200)	(0.224)	(0.196)
employed	0.146	0.524	0.0288
	(0.360)	(0.418)	(0.418)
Ewe	0.238	-0.107	0.451
	(0.498)	(0.517)	(0.505)
Ga	-0.599	0.170	0.198
	(0.384)	(0.404)	(0.517)
other ethnicity	0.604	0.703	0.381
	(0.529)	(0.470)	(0.482)
AoG Abundant Life	-0.870*	-0.888	-1.146*
	(0.500)	(0.667)	(0.601)
AoG Redemption	-1.086**	-1.687***	-1.337**
	(0.549)	(0.605)	(0.638)
AoG Faith Chapel	0.115	-0.245	-0.198
	(0.526)	(0.633)	(0.650)
AoG Sanctuary	0.605	0.349	-0.157
	(0.478)	(0.580)	(0.515)
AoG Shammah	-0.0715	-0.388	-0.560
	(0.600)	(0.611)	(0.614)
Dchurchother	0.817*	0.424	0.00458
	(0.468)	(0.843)	(0.538)
Constant	4.928***	7.070***	6.043***
	(1.148)	(1.267)	(1.295)
Observations	404	404	404

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.11: Non-anonymous church giving

	(1) Giving to Church named (vs keep)
model	
Insurance	-1.013**
	(0.473)
No insurance	-0.548
	(0.493)
Constant	5.607***
	(0.413)
Observations	454

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.12: Treatment effects for other dictator games

	(1) Thanks (vs church)	(2) Street (vs church)	(3) Thanks (vs street)
model			
Insurance	-0.082	0.006	-0.255
	(0.330)	(0.271)	(0.266)
No insurance	0.093	0.169	-0.127
	(0.335)	(0.258)	(0.254)
Constant	4.901***	5.702***	4.841***
	(0.249)	(0.205)	(0.185)
Observations	454	454	454

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.13: Treatment effects for giving to thanksgiving for total sample (column 1) and revival week only (colmun 2)

	(1) Giving to thanks.	(2) Giving to thanks.
model		
Insurance	-1.036*	1.819***
	(0.529)	(0.326)
No insurance	-0.976**	1.869*
	(0.471)	(1.018)
Revival week	-2.716***	
	(0.497)	
Revival week X Insurance	2.964***	
	(0.677)	
Revival week X No insurance	3.004***	
	(1.092)	
female	-0.0411	1.055
	(0.305)	(0.728)
age	-0.00473	0.00977
	(0.0125)	(0.0209)
log(income)	-0.0714	-0.0555
	(0.196)	(0.332)
higher education	-0.0339	0.110
	(0.340)	(0.563)
employed	0.764**	1.312**
	(0.338)	(0.586)
Ewe	0.0800	0.749
	(0.406)	(0.703)
Ga	0.198	0.703
	(0.448)	(1.086)
other ethnicity	0.895**	1.111
	(0.381)	(0.756)
Constant	5.768***	1.240
	(1.079)	(1.529)
Observations	521	117

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.14: Treatment effects for giving to Street Children Fund for total sample (column 1) and revival week only (colmun 2)

	(1) Giving to street.	(2) Giving to street.
model		
Insurance	-1.004**	1.779***
	(0.433)	(0.456)
No insurance	-1.134**	1.405*
	(0.465)	(0.716)
Revival week	-2.464***	
	(0.465)	
Revival week X Insurance	2.741***	
	(0.574)	
Revival week X No insurance	2.557***	
	(0.838)	
female	-0.459	0.406
	(0.382)	(0.669)
age	0.00279	0.0156
	(0.0135)	(0.0245)
log(income)	0.247	0.234
	(0.171)	(0.307)
higher education	-0.156	0.777
	(0.375)	(0.662)
employed	0.203	0.669
	(0.346)	(0.581)
Ewe	0.615	0.998
	(0.397)	(0.745)
Ga	0.236	0.673
	(0.480)	(0.910)
other ethnicity	0.473	0.593
	(0.385)	(0.592)
Constant	4.890***	0.755
	(1.073)	(1.771)
Observations	521	117

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.15: Comparing revival church members and church members giving relatively high amounts to the church

	(1) Giving to church	(2) Giving to thanks.	(3) Giving to street.
model			
Insurance	-0.952*	-1.233**	-1.220**
	(0.544)	(0.591)	(0.490)
No insurance	-1.196**	-1.393***	-1.331***
	(0.525)	(0.479)	(0.477)
High givers	-0.976*	-1.697***	-1.675***
	(0.570)	(0.560)	(0.554)
High givers X Insurance	0.634	1.267	1.285
	(0.858)	(0.818)	(0.820)
High givers X No insurance	1.388*	2.425***	0.981
	(0.784)	(0.813)	(0.818)
Revival week	-1.925***	-2.505***	-2.411***
	(0.626)	(0.494)	(0.454)
Revival week X Insurance	2.840***	3.004***	2.919***
	(0.954)	(0.743)	(0.536)
Revival week X No insurance	2.296**	2.465**	2.225***
	(1.024)	(0.971)	(0.722)
Constant	6.124***	6.149***	6.698***
	(0.463)	(0.437)	(0.391)
Observations	514	514	514

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3.16: Comparing revival church members and church members giving relatively high amounts to the church, controlling for church involvment

	(1) Giving to church	(2) Giving to thanks.	(3) Giving to street.
model			
Insurance	-0.955*	-1.197**	-1.229**
	(0.540)	(0.599)	(0.487)
No insurance	-1.198**	-1.354***	-1.333***
	(0.521)	(0.499)	(0.477)
High givers	-0.750	-1.635**	-1.307**
	(0.644)	(0.656)	(0.633)
High givers X Insurance	0.609	1.173	1.290
	(0.872)	(0.802)	(0.825)
High givers X No insurance	1.358*	2.373***	0.991
	(0.788)	(0.812)	(0.815)
Revival week	-1.893***	-2.436***	-2.376***
	(0.620)	(0.491)	(0.443)
Revival week X Insurance	2.800***	2.833***	2.872***
	(0.939)	(0.727)	(0.526)
Revival week X No insurance	2.293**	2.424**	2.191***
	(1.013)	(0.989)	(0.744)
employed	0.273	0.478	0.0471
	(0.313)	(0.307)	(0.318)
log(income)	0.113	-0.177	0.200
	(0.197)	(0.248)	(0.208)
going to church daily	-0.128	-0.925*	-0.764
	(0.569)	(0.553)	(0.602)
church_sevweekly	-0.0586	-0.785**	-0.697
	(0.414)	(0.357)	(0.423)
frequent prayer	0.0404	0.787	-0.278
	(0.559)	(0.548)	(0.564)
Constant	5.307***	6.699***	6.293***
	(1.307)	(1.366)	(1.298)
Observations	514	514	514

Note: Tobit regression censored at 0 and 11. Dependent variables measure donations intended for the own church branch, the street children's fund (secular NGO) and the Inter-denominational Thanksgiving (religious NGO) with the alternative option to keep the money. Standard errors (between parenthesis) are clustered at session level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

3.8.2 Model Appendix

Setup

We assume that a church member has an income of Y and chooses to give an amount g to the church. The church member enjoys utility $u(.)$ from consuming secular goods, and utility $\theta f(.)$ from consuming church goods. Thus a church member who gives g to the church enjoys a total utility of $u(Y-g)+\theta f(g)$. Both utility functions are concave, thrice differentiable, and increasing in their arguments. In each period church members face a probability π of an income loss of size D.

Under the assumption that insurance is offered through the church community, church giving also has the impact of reducing the size of the loss, thus the total loss would be $D-l(g)$. The function $l(g)$ is assumed to be increasing and concave. Under the assumption that church members believe in spiritual insurance, this probability is decomposed into a basic probability of loss $\tilde{\pi}$, and a portion of the loss that can be mitigated by giving money to spiritual goods. Therefore, the total subjective probability of giving is $\pi=\tilde{\pi}-p(g)$.

Optimal giving to the church in the absence of any insurance

In this section we assume that church members choose a particular level of giving to maximise their total expected utility. There is no insurance offered through the church.

$$\max_{g} \quad (1-\pi)u(Y-g)+\pi u(Y-g-D)+\theta f(g) \tag{3.7}$$

This leads to the following first order condition:

$$(\pi-1)u'(Y-g)-\pi u'(Y-g-D)+\theta f'(g)=0 \tag{3.8}$$

Rewriting the FOC in terms of $g^*(D,\theta)$,

$$(\pi-1)u'(Y-g^*(D,\theta))-\pi u'(Y-g^*(D,\theta)-D)+\theta f'(g^*(D,\theta))=0 \tag{3.9}$$

This equation implicitly defines the optimal giving g^*, which is a function of the expected loss D and θ.

We want to know the impact of experimentally manipulating D on the level of giving of individuals, in other terms the sign of $\frac{\partial g^*(D,\theta)}{\partial D}$.

Let $g_D^{*'}(D,\theta) = \frac{\partial g^*(D,\theta)}{\partial D}$. Taking the derivative of the FOC with respect to D leads to the following equality:

$$g_D^{*'}(D,\theta) * [\pi[u''(Y-g^*-D) - u''(Y-g^*)] + u''(Y-g^*) + \theta f''(g^*)] = -\pi u''(Y-g^*-D) \quad (3.10)$$

The right-hand side of the expression is *positive*. Each individual term of the expression multiplied by $g_D^{*'}$ is *negative*. Therefore $g_D^{*'}$ must also be *negative*.

Let us call $g_\theta^{*'} = \frac{\partial g^*(D,\theta)}{\partial \theta}$. We can also show that $g_\theta^{*'}$ is positive: a positive shock on the utility from consuming church goods increases church donations. Taking the derivative of the FOC with respect to θ leads to the following equality:

$$g_\theta^{*'}(D,\theta) * [(1-\pi)u''(Y-g^*) + \pi u''(Y-g^*-D) + \theta f''(g^*)] = -f'(g^*) \quad (3.11)$$

The right-hand side of the expression is *negative*. Each individual term of the expression multiplied by $g_\theta^{*'}$ is *negative*. Therefore $g_\theta^{*'}$ is *positive*.

Community insurance: optimal giving when giving reduces the size of a loss

In this section we assume that giving to church reduces the size of the loss. $L = D - l(g)$ This assumption illustrates the channel of community insurance.

$$\max_g \quad (1-\pi)u(Y-g) + \pi u(Y-g-D+l(g)) + \theta f(g) \quad (3.12)$$

This leads to the following first order condition:

$$(\pi - 1)u'(Y - g) + \pi(-1 + l'(g))u'(Y - g - D + l(g)) + \theta f'(g) = 0 \tag{3.13}$$

Rewriting the FOC in terms of $g^*(D, \theta)$:

$$(\pi - 1)u'(Y - g^*(D,\theta))) + \pi(-1 + l'(g^*(D,\theta)))u'(Y - g^*(D,\theta) - D + l(g^*(D,\theta))) \\ + \theta f'(g^*(D,\theta))) = 0 \tag{3.14}$$

Taking the derivative of the FOC with respect to D leads to the following equality:

$$g_D^{*'} * [(1 - \pi)u''(Y - g^*) + \pi(l'(g^*) - 1)^2 u''(Y - g^* - D + l(g^*)) \\ + \pi l''(g^*)u'(Y - g - D + l(g^*)) + \theta f''(g^*)] = \pi(l'(g^*) - 1)u''(Y - g^* - D + l(g)) \tag{3.15}$$

On the right-hand side $u''(Y - g^* - D + l(g))$ is always *negative* while the expression multiplied by $g_D^{*'}$ of the left-hand side is also always *negative*. Therefore the sign of $g_D^{*'}$ depends on $(l'(g^*) - 1)$.

This provides a relationship between the efficiency of community based insurance and the optimal response of giving.

$$g_D^{*'} > 0 \text{ when } l'(g^*) > 1, \text{ or } g^* < l'^{-1}(1) \tag{3.16}$$

and

$$g_D^{*'} \leq 0 \text{ when } l'(g^*) \leq 1, \text{ or } g^* \geq l'^{-1}(1) \tag{3.17}$$

These conditions tell us that for low levels of optimal giving, experimentally increasing the perceived loss D will decrease optimal giving.

We show below that the variation in optimal giving g^* can be the result of a variation in θ. More particularly, we demonstrate that $g_\theta^{*'} > 0$. Taking the derivative of the FOC with respect to

θ gives:

$$g_\theta^{*'} * [(1-\pi)u''(Y-g^*) + \pi l''(g^*)u'(Y-g^*-D+l(g^*)) \\ + \pi(-1+l'(g^*))^2 u''(Y-g^*-D+l(g^*)) + \theta f''(g^*)] = -f'(g^*) \quad (3.18)$$

The right-hand side of the expression is *negative*. Each individual term of the expression multiplied by $g_\theta^{*'}$ is *negative*. Therefore $g_\theta^{*'}$ is *positive*.

Therefore our model predicts that there exist a threshold level for θ that will trigger a switch in the sign of $g_D^{*'}$.

Numerical illustration Graphs 3.2 and 3.3 illustrate a numerical example, in which we simulate the case of $g_D^{'*}(D,\theta)$ changing sign around the threshold $\tilde{\theta}$.

This example uses a CARA utility function ($u(c) = 1 - exp(-ac)$), and assumes that $l(g) = s\ log(1+g)$. The parameters D, s are chosen such that $D - l(g) \geq 0$. Figure 3.2 shows that the optimal giving $g^*(D,\theta)$ is increasing in θ while Figure 3.3 indicates that $g^*(D,\theta)$ is an increasing function of D until the threshold $\tilde{\theta} = 0.345$.

Spiritual insurance: optimal giving when giving reduces the subjective probability of a loss

In this section we assume that giving reduces the size of the loss. $\pi = \tilde{\pi} - p(g)$ This assumption illustrates the channel of spiritual insurance.

$$\max_g \quad (1-\tilde{\pi}+p(g))u(Y-g) + (\tilde{\pi}-p(g))u(Y-g-D) + \theta f(g) \quad (3.19)$$

This leads to the following first order condition:

$$p'(g)u(Y-g) - (1-\tilde{\pi}+p(g))u'(Y-g) - p'(g)u(Y-g-D) - (\tilde{\pi}-p(g))u'(Y-g-D) + \theta f'(g) = 0 \quad (3.20)$$

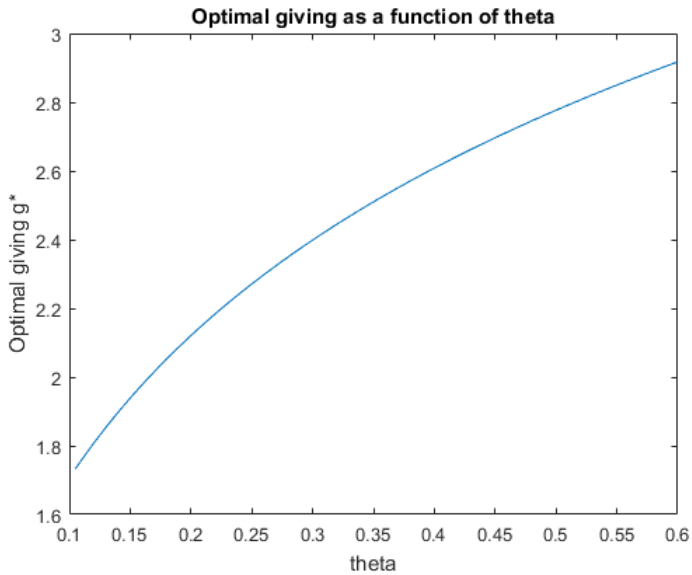


Figure 3.2: Community insurance - Numerical example: $Y = 10$, $D = 8$, $\pi = 0.4$, $u(.)$ CARA with $a = 0.1$, $f(.)$ CARA with $a = 1$, and $l(.)$ a logarithmic function with $s = 3.5$

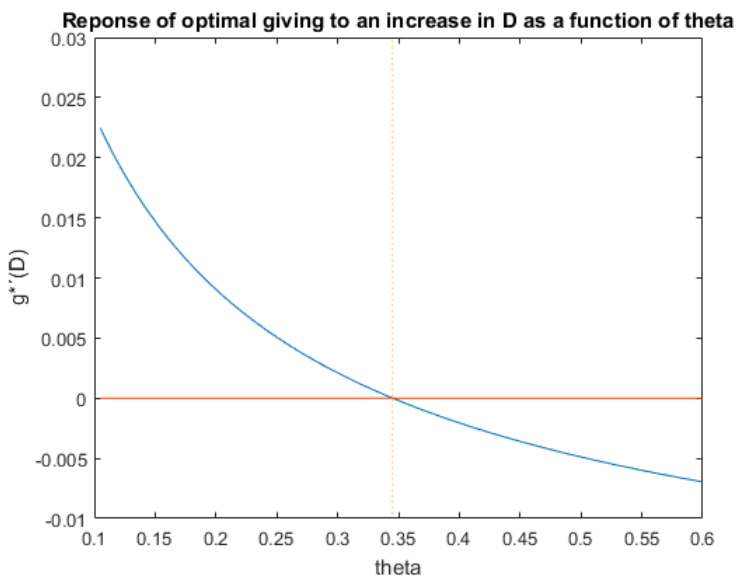


Figure 3.3: Community insurance - $g^{*'}(D)$ as a function of θ - numerical example marking the threshold $\tilde{\theta}$ where the sign of $g^{*'}(D)$ changes from positive to negative

Rewriting the FOC in terms of $g^*(D,\theta)$,

$$p'(g^*(D,\theta))u(Y-g^*(D,\theta)) - (1-\tilde{\pi}+p(g^*(D,\theta)))u'(Y-g^*(D,\theta)) -$$
$$p'(g^*(D,\theta))u(Y-g^*(D,\theta)-D) - (\tilde{\pi}-p(g^*(D,\theta)))u'(Y-g^*(D,\theta)-D) + \theta f'(g^*(D,\theta)) = 0 \tag{3.21}$$

Taking the derivative of the FOC with respect to D leads to the following equality:

$$\begin{aligned} g_D^{*'} * [p''(g^*)[u(Y-g^*) - u(Y-g^*-D)] + 2p'(g^*)[u'(Y-g^*-D) - u'(Y-g*)] \\ + (\tilde{\pi}-p(g^*))[u''(Y-g^*-D) - u''(Y-g^*)] + u''(Y-g^*) + f''(g)] \\ = -[p'(g^*)u'(Y-g*-D) + (\tilde{\pi}-p(g))u''(Y-g^*-D)] \end{aligned} \tag{3.22}$$

Therefore, we have the following conditions:

$$g_D^{*'} > 0 \text{ when } -[p'(g^*)u'(Y-g*-D) + (\tilde{\pi}-p(g))u''(Y-g^*-D)] < 0 \tag{3.23}$$

$$g_D^{*'} < 0 \text{ when } -[p'(g^*)u'(Y-g*-D) + (\tilde{\pi}-p(g))u''(Y-g^*-D)] > 0 \tag{3.24}$$

Numerical illustration We simplify these conditions using a CARA utility function: $u(c) = 1-e^{-ac}$, $u'(c) = ae^{-ac}$, $u''(c) = -a^2e^{-ac}$ and the risk aversion $R(c) = -\dfrac{u''(c)}{u'(c)} = a$

$$-p'(g) - (\pi - p(g))\frac{u''(Y-g-D)}{u'(Y-g-D)} = -p'(g) + (\tilde{\pi}-p(g))a \tag{3.25}$$

Therefore:

$$g_D^{*'} > 0 \text{ when } -p'(g^*) + (\tilde{\pi}-p(g^*))a < 0 \tag{3.26}$$

$$g_D^{*'} < 0 \text{ when } -p'(g^*) + (\tilde{\pi} - p(g^*))a > 0 \tag{3.27}$$

which can be rewritten as:

$$g_D^{*'} > 0 \text{ when } \frac{1}{a}p'(g^*) > (\tilde{\pi} - p(g^*)) \tag{3.28}$$

$$g_D^{*'} < 0 \text{ when } \frac{1}{a}p'(g^*) < (\tilde{\pi} - p(g^*)) \tag{3.29}$$

Therefore, we find that $g_D^{*'}$ is positive when the effectiveness of the spiritual insurance divided by the coefficient of absolute risk aversion at g^* is greater than the level of risk at g^*.

We can now also derive the conditions under which $g_D^{*'}$ is increasing until a certain level, and then decreasing. For this, we use the following reformulation of conditions (3.30) and (3.31):

$$g_D^{*'} > 0 \text{ when } p'(g^*) + ap(g^*) > a\tilde{\pi} \tag{3.30}$$

$$g_D^{*'} < 0 \text{ when } p'(g^*) + ap(g^*) < a\tilde{\pi} \tag{3.31}$$

Let us define $\Gamma(g) = p'(g) + ap(g)$. For $g_D^{*'}$ to be first positive and then negative we need $\Gamma(g)$ to be decreasing:

$$g_D^{*'} > 0 \text{ when } g^* < \Gamma^{-1}(a\pi) \tag{3.32}$$

$$g_D^{*'} < 0 \text{ when } g^* > \Gamma^{-1}(a\pi) \tag{3.33}$$

In order for Γ' to be decreasing, we need the following condition to be true:

$$\Gamma'(g) \leq 0 \Leftrightarrow p''(g) + ap'(g) \leq 0 \tag{3.34}$$

In the following, we will use a parametrization of $p(g)$ that is concave, and an a such that condition (3.34) hold in order to illustrate that with an increase in the level of giving, due to a higher θ for example, the sign of $g_D^{*'}$ can reverse.

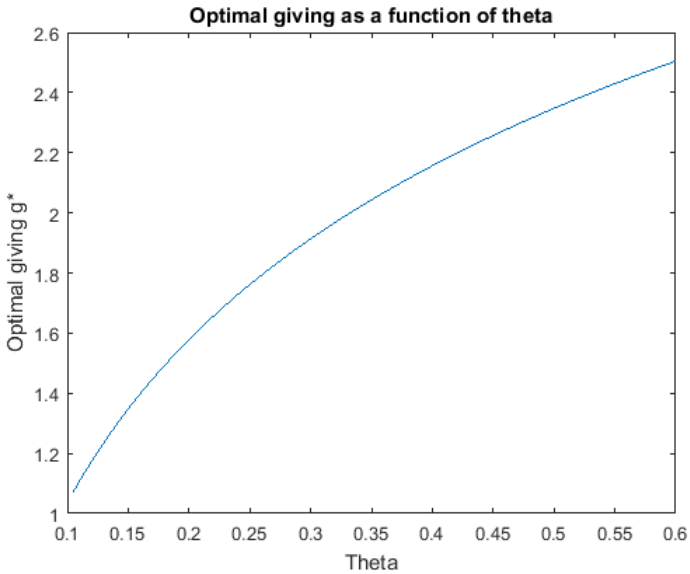


Figure 3.4: Numerical example: $Y = 10$, $D = 8$, $\pi = 0.4$, $u(.)$ CARA with $a = 0.1$, $f(.)$ CARA with $a = 1$, and $p(.)$ a logarithmic function with $k = 0.09$

We know that g^* is a function of θ, and we will now show a numerical example that illustrates the possibility of $g_D^{*'}|_{g^*(\theta)}$ to be positive until $g^*(\tilde{\theta})$ and negative afterwards. We will use the a simple logarithmic function $p(g) = klog(g+1)$ where $\tilde{\pi}$ and k are such that $0 < \tilde{\pi} - p(g) < 1$. If we insert this into equation (3.30), we get:

$$-\frac{k}{g^*(\theta)+1} + (\tilde{\pi} - klog(g^*(\theta)+1))a < 0 \tag{3.35}$$

Together with (3.31), we know that at a specific $\tilde{\theta}$, this equation is equal to zero:

$$-\frac{k}{g^*(\tilde{\theta})+1} + (\tilde{\pi} - klog(g^*(\tilde{\theta})+1))a = 0 \tag{3.36}$$

The following graphs illustrate a numerical example, in which we simulate the case of $g^*(\theta)$ being around the threshold in (3.36).

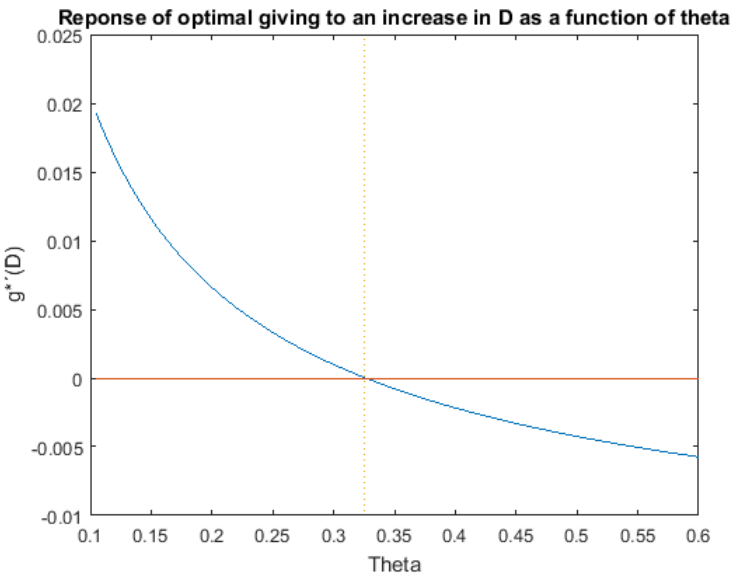


Figure 3.5: $g^{*'}(D)$ as a function of θ - numerical example marking the threshold $\tilde{\theta}$ where the sign of $g^{*'}(D)$ changes from positive to negative

Chapter 4

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