

Essays in Financial Decision Making

D I S S E R T A T I O N
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences,
International Affairs and Computer Science
to obtain the title of
Doctor of Philosophy in Economics and Finance

submitted by

Immanuel Lampe

from

Germany

Approved on the application of

Prof. Dr. Martin Brown

and

Prof. Dr. Stefan Trautmann

Dissertation no. 5228

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The University of St.Gallen, School of Management, Economics, Law, Social Sciences, International Affairs and Computer Science, hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St.Gallen, June 13, 2022

The President:

Prof. Dr. Bernhard Ehrenzeller

*To my wonderful family and
my wonderful girlfriend*

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Merzhausen, July 24th 2022

Immanuel Lampe

Summary

This thesis contains three essays on the role of economic preferences (risk, uncertainty, time) in financial decision making. The first two essays examine whether economic preferences can help to explain the low demand for two highly relevant insurance products. The third project investigates how people make decisions in contexts that involve both, a risk and a time dimension.

The thesis employs different data sources and methodologies. For the first two project the thesis links data that allows to elicit economic preferences with data on insurance demand decisions. The results of the first project suggest that a combination of an aversion towards losses and limited understanding of the insurance helps to explain the low demand for highly subsidized agricultural insurance products in developing countries. The second project investigates how time-and risk-preferences influence the demand for private long-term care insurance in the US. The results of this project suggest that consumers, who strongly discount payouts that arrive in the future, perceive private long-term care insurances as less attractive and are therefore less likely to buy these products.

Several economic decisions affect outcomes in several time periods. If, for instance, people decide to save money for retirement, then this has consequences for the current consumption profile but also for the consumption profile in the future. These decisions are referred to as intertemporal decisions. For the third project a large economic experiment was conducted on a sample that is representative of the Dutch population. The results of this projects allow conclusions about how one of the most famous economic theory of decision making under risk (Prospect Theory) should be applied to a context in which payouts arrive at different points in time.

Zusammenfassung

Diese Dissertation besteht aus drei Projekten zur Rolle von ökonomischen Präferenzen (Risiko, Unsicherheit, Zeit) in finanziellen Entscheidungen. Die ersten zwei Projekte untersuchen, ob ökonomische Präferenzen helfen können die geringer Nachfrage nach zwei hoch relevanten Versicherungen zu erklären. Das dritte Papier untersucht wie Menschen Entscheidungen in Kontexten treffen, die sowohl eine Risiko- als auch eine Zeitkomponente enthalten.

In der Dissertation werden verschiedenste Datenquellen und Methodiken verwendet. Für die ersten zwei Forschungsprojekten werden Daten, die es erlauben ökonomische Präferenzen von Menschen zu messen, mit Versicherungsnachfragedaten verknüpft. Die Ergebnisse des ersten Projekts legen nahe, dass eine Kombination aus einer Aversion gegenüber Verlusten und einem geringem Versicherungsverständnis dabei hilft die geringe Nachfrage nach stark subventionierten Agrarversicherungprodukten in Entwicklungsländern zu erklären. Das zweite Projekt untersucht wie Risiko- und Zeitpräferenzen die Nachfrage nach privaten Pflegeversicherungen in den USA beeinflussen. Die Ergebnisse legen nahe, dass Menschen, die zukünftige Auszahlungen stark diskontieren, eine Pflegeversicherung als wenig attraktiv erachten und diese daher nicht abschliessen.

Viele volkswirtschaftliche Entscheidungen haben Konsequenzen für mehrere Zeitperioden. Wenn Personen beispielsweise für die Rente sparen, so beeinflusst dies das Konsumprofil in der Gegenwart aber auch das Konsumprofil in der Zukunft. Solche Situation werden als intertemporelle Entscheidungen bezeichnet. Für das dritte Projekt wurde ein grosses ökonomisches Entscheidungsexperiment auf einer repräsentativen Stichprobe der niederländischen Bevölkerung durchgeführt. Die Ergebnisse dieses Projekts erlauben Rückschlüsse darüber, wie eine der bekanntesten volkswirtschaftlichen Theorien zur Modellierung von Entscheidungen unter Risiko (Prospect Theory) in einem intertemporellen Kontext angewendet werden sollte.

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Chapter 1

Loss Aversion and the Demand for Index Insurance

Immanuel Lampe & Daniel Wüertenberger

Abstract

This work analyzes if reference dependence and loss aversion can explain the puzzling low adoption rates of rainfall index insurance. We present a model that predicts the impact of loss aversion on index insurance demand to vary with different levels of insurance understanding. Index insurance demand of farmers who are unaware of the loss-hedging benefit that insurance provides decreases with loss aversion. In contrast, insurance demand of farmers who are aware of the loss-hedging benefit increases with loss aversion. The model further predicts that farmers who are unaware of the loss-hedging benefit will not demand an even highly subsidized index insurance. Using data from a randomized controlled trial involving a sample of Indian farmers we provide empirical support for our core conjecture that insurance understanding mitigates the negative impact of loss aversion on index insurance adoption.

1.1 Introduction

The economies of most developing countries are highly dependent on agriculture. The agricultural sector in Africa, for example, accounts for more than 50% of the total employment on the continent (Patt, Suarez, and Hess, 2010). Furthermore, this sector faces inherent weather risks (Hyman et al., 2008; Cooper et al., 2008; Barrett and Santos, 2014; Hansen et al., 2018). Accordingly, formal financial hedges that smooth agricultural income between periods with good and bad weather conditions are regarded as a prerequisite for sustainable economic growth. One particular type of formal financial hedge offered in many developing countries is index insurance. Index rainfall insurance underwrites an indemnity payment depending on the realized rainfall at the farmer's nearest weather station. The advantages are, first, a low premium because of low administrative costs and, second, the absence of moral hazard and adverse selection (Giné, Townsend, and Vickery, 2008; Carter et al., 2014). The main drawback of index insurance is that payouts are not perfectly correlated with farmer's harvest loss. This lack of correlation is known as basis risk. Basis risk is particularly pronounced if the weather stations are too far away from farmer's field (Würtenberger, 2017). Given the inherent riskiness of farming, the low and stagnating take-up rates of about 20% are puzzling and cannot be explained by standard expected utility models of insurance demand (Hellmuth et al., 2009; Patt, Suarez, and Hess, 2010; Karlan et al., 2014).¹

This paper takes a behavioral economics approach to explain the low demand for index insurance. In particular, we incorporate two of the four ingredients of Kahneman and Tversky's (1979) Prospect Theory (hereafter PT); namely, reference dependence and loss aversion.² According to Barberis (2013), it is often unclear how to define precisely what a subjective gain or loss is. Therefore, the central challenge in the application of PT is the choice of appropriate reference points. In our index insurance demand model we choose two reference points which we believe are reasonable choices for two different types of farmers: naive and insurance-literate farmers.

¹If the index insurance is offered at an actuarially fair price, the estimated take-up rates range from 25% (Cole et al., 2013) to 11% (Karlan et al., 2014) and even 6.4% (Gaurav, Cole, and Tobacman, 2011). Take-up rates increase to about 35% if the insurance is offered at a price equal to 50% of its actuarially fair value (Karlan et al., 2014; Mobarak and Rosenzweig, 2012). Previous research showing considerable welfare gains for farmers holding index insurance contracts (Cole, Giné, and Vickery, 2017; Carter, Cheng, and Sarris, 2016) makes these low rates even more puzzling.

²According to Barberis (2013), PT consist of four aspects: reference dependence, loss aversion, diminishing sensitivity and probability weighting.

The purpose of insurance is to alleviate the impact of losses. Therefore, the demand for insurance depends on how an individual assesses the benefit of alleviating the impact of losses versus the cost of the insurance premium (Brown and Finkelstein, 2008; Gottlieb and Mitchell, 2020). Additionally, it is likely that this assessment depends on the level of insurance understanding (Giné and Yang, 2009; Gaurav, Cole, and Tobacman, 2011). Consistent with this view, we distinguish between naive farmers who do not understand how insurance works and insurance-literate farmers who do. We assume that naive farmers are not aware of the loss-hedging benefit that index insurance provides. Instead, they regard index insurance as an uncertain investment that is not related to the actual harvest loss. Thus, naive farmers compare the outcomes of the index insurance to not investing at all, which constitutes a natural reference point for these farmers. This means if no loss occurs - and, thus, no indemnity is paid out - the premium is perceived as a pure loss. This view of 'insurance as investment' rather than a loss-hedging device is supported by Patt et al. (2009), who report that some farmers are upset if the indemnity payment is less than the premium paid for the insurance. In contrast, insurance-literate farmers are aware of the loss-hedging benefit of index insurance. Accordingly, these farmers only expect an indemnity payment in case of harvest loss. A natural reference point to model this situation is coverage of a (perfect) insurance which, if a loss occurs, always pays out. These two distinct reference points propose different influences of loss aversion on index insurance demand. Our PT model predicts that insurance demand of naive farmers is decreasing with loss aversion, whereas it is increasing with loss aversion for insurance-literate farmers. Furthermore, our model suggests that naive farmers whose preferences are characterized by median values of the PT parameters do not demand index insurance even if it is highly subsidized.

We take the predictions of our model to the data, revisiting Cole et al.'s (2013) evidence on index insurance demand of farmers in a rural region of India. Cole et al. (2013) randomly assigned an insurance education module to a subsample of 350 out of 1,042 farmers. We utilize this treatment as an exogenous variation of farmers' level of insurance understanding and, therefore, awareness of the loss-hedging benefit that insurance provides. The dataset captures measures of insurance demand, information on financial socialization and information on the socio-economic background. Furthermore, farmers were asked to choose among lotteries varying in risk and expected return. Following Bin-

swanger (1981), Cole et al. (2013) interpret lottery choices as indicators of risk aversion. The payouts of the experimental choice task are small relative to farmers' real world income.³ Accordingly, lottery choices are only suitable to elicit risk attitudes if farmers are assumed to isolate the income from the choice task from lifetime income (Rabin, 2000). We follow other experimental studies (Fehr and Goette, 2007; Gächter, Johnson, and Herrmann, 2007) and assume that farmers integrate the experimental income with their lifetime income. Imposing further strict assumptions we show that lottery choices may also indicate loss aversion. We document substantial differences in the impact of loss aversion on insurance demand between farmers in the treatment and in the control group. Insurance demand of farmers in the control group decreases with loss aversion. An increase in loss aversion by one standard deviation decreases the likelihood to demand at least one insurance contract by between 2.6 and 3.5 percentage points. Given an overall take-up rate of 30.2%, these effects are economically meaningful. The negative effect vanishes for farmers in the treatment group.⁴ Due to its specific design, the education module positively affects the awareness of the loss-hedging benefit that insurance provides. Furthermore, it is unlikely that the insurance education treatment impacts the relationship between loss aversion and insurance demand other than by increasing the overall awareness of the loss-hedging benefit. Thus, our findings support our conjecture that the impact of loss aversion on insurance demand varies systematically with the level of product understanding.

Our paper contributes to three main strands of literature. First, we add to the recent literature on the impact of economic preferences on the demand for index insurance products. Clarke (2016) presents a rational demand model that assumes imperfect correlation between insurance net transfer and farmers' net loss (basis risk). This model only explains the observed low insurance take-up of the most risk-averse farmers (Giné, Townsend, and Vickery, 2008) as a rational response to the risk of contract non-performance. In contrast to Clarke (2016), we focus on loss instead of risk aversion.⁵ To the best of our knowledge,

³The payoffs of the choice task range between Rs. 0 – 110 whereas farmers' mean (median) yearly income is Rs. 57,991 (34,116). Thus, the maximum income from the choice task amounts to 2.3% ($= 12 \cdot 110/57,991$) of the average monthly income. Accordingly, stakes are much smaller than in the high-stake decision task of Binswanger (1981) with stakes amounting to a month's average income.

⁴In some specifications, the effect turns positive and an increase in loss aversion by one standard deviation increases the likelihood to demand at least one insurance contract by between 2.2 and 3.7 percentage points.

⁵The scenario in which a farmer buys an insurance and still suffers a loss without indemnity payment is a natural starting point to include loss aversion.

the impact of loss aversion on index insurance demand has not yet been analyzed. Thus, we add to this literature by highlighting the role of loss aversion.

Second, we contribute to the research on the role of PT preferences in insurance demand decisions. Most of the literature focuses on probability weighting (Sydnor, 2010; Barseghyan et al., 2013) and neglects loss aversion. Recent studies by Gottlieb and Mitchell (2020) and Hwang (2016) include loss aversion and present similar models to ours and empirically find a negative impact of narrow framing and loss aversion on the demand for long-term care insurances in the US. To the best of our knowledge, we are the first to analyze the impact of loss aversion on insurance demand within a setting that includes a contract non-performance risk.

Third, we contribute to the literature on the role of loss aversion as well as product understanding for technology adoption. Liu (2013) finds that loss aversion is one of the main drivers for the sluggish adoption of a new and superior crop among Chinese farmers. Emerick et al. (2016) find that adoption of a new seed variety among farmers in rural Indian villages is increasing with understanding of the product. The assumption that the decision to adopt a familiar product might require a different reference point than the decision to adopt an unfamiliar product seems tautological. However, to the best of our knowledge, there is not extant research that combines loss aversion and product understanding. We contribute to this literature by documenting that product understanding mitigates the negative impact of loss aversion on technology adoption.⁶

The remainder of this paper is organized as follows. Section 2 introduces our behavioral index insurance demand model. Section 3 presents the data and the empirical test of our core hypothesis. Section 4 discusses shortcomings of the model and the empirical specification. Section 5 concludes.

1.2 Behavioral Insurance Demand Model

We focus on a model with only four states of the world. A loss L occurs with probability p . In a classical insurance setting the loss would trigger an indemnity payment I . To account for the specific feature of an index insurance, the basis risk, we assume

⁶Given the high level of loss aversion (Liu, 2013; Holden and Quiggin, 2017) accompanied by the low level of education in developing countries (Cole et al., 2013), we offer meaningful new insights to explain the low technology adoption rates (Brick and Visser, 2015; Abay, Blalock, and Berhane, 2017) in the developing world.

that, given a loss, there is a probability $q_1 > 0$ that the insurance does not pay out the indemnity payment. We refer to this state as the downside basis risk. Similarly, to include the upside basis risk, we assume that, given no loss, there is a probability $q_2 > 0$ that the insurance does pay out the indemnity payment. Table 1.1 illustrates the four states and the associated probabilities.]

	Indemnity	No Indemnity
Loss	$p(1 - q_1)$	pq_1
No Loss	$(1 - p)q_2$	$(1 - p)(1 - q_2)$

Notes: The table summarizes the four states of the model and the associated probabilities.

Table 1.1: Four state framework (probabilities)

We assume that the probabilities the insurance under- or overestimates the actual loss are the same, i.e., $pq_1 = (1 - p)q_2$.⁷ We denote these probabilities by r . We label farmer's initial wealth level with W and, finally, assume that the premium Π is actuarially fair, i.e., $\Pi = pI$. Table 1.2 assigns labels ((1) – (4)) to the different states and summarizes the outcomes for a farmer who does not demand and a farmer who does demand the insurance.

State	Loss		No Loss	
	Indemnity (1)	No Indemnity (2)	Indemnity (3)	No Indemnity (4)
Probability	$p(1 - q_1)$	r	r	$(1 - p)(1 - q_2)$
Wealth, No Insurance	$W - L$	$W - L$	W	W
Wealth, Index Insurance	$W - pI - L + I$	$W - pI - L$	$W - pI + I$	$W - pI$

Notes: The tables summarizes the probabilities and outcomes of each state.

Table 1.2: Four state framework (probabilities and outcomes)

We assume that farmers do not obey asset integration. Instead, they evaluate monetary outcomes in terms of gains and losses with respect to some reference point. According to PT, farmers' value function equals

$$v(x) = \begin{cases} (x - R)^\alpha & , \text{ if } x \geq R \\ -\lambda(R - x)^\alpha & , \text{ if } x < R. \end{cases} \quad (1.1)$$

⁷Under this assumption the probability that the index insurance pays out is p . Thus, the index insurance indemnity payment is an unbiased approximation of the indemnity payment of an insurance without the existence of basis risk. This assumption is supported by the empirical findings of Clarke et al. (2012).

In the value function (1.1), R is the reference point, α the coefficient of diminishing marginal sensitivity for gains and losses and λ the coefficient of loss aversion.⁸ The crucial issue within the application of PT is the choice of an appropriate reference point. Wakker, Thaler, and Tversky (1997) and Sydnor (2010) use initial wealth W as a reference point. However, the main problem with this reference point is, as Sydnor (2010) argues, the fact that the decision to demand insurance is then entirely determined in the loss domain. Thus, initial wealth is a questionable choice.⁹ In many other applications of PT in economics, the reference point is set as the status quo. In the index insurance context the status quo (= no coverage) is state dependent. It equals either W or $W - L$. Consequently, a possibly reasonable choice of the reference point might be $W - L$ for the state in which the loss L occurs and W for the state in which no loss occurs. We refer to this reference point as 'No Insurance Coverage' and analyze the implications of its choice in Section 1.2.1.¹⁰ Several empirical findings suggest that the status quo might not necessarily be an appropriate choice. Instead, it seems that individuals often choose risk-free outcomes as the reference point (for a review see Schmidt (2016)). Accordingly, Schmidt (2016) proposes full insurance coverage as an alternative reference point. The index insurance setting is special in the sense that, although a farmer is insured, he might, because of the basis risk, still suffer from an unsecured loss. Thus, index insurance coverage is not a risk-free outcome. Accordingly, we choose full coverage of a perfect insurance that always pays out in the case of a loss but never pays out in case of no loss as a second reference point. We refer to this reference point as 'Perfect Insurance Coverage' and analyze the implications of its choice in Section 1.2.2.

1.2.1 No Insurance Coverage

We first analyze insurance demand with a state-dependent reference point given by wealth without any insurance. Hence, the reference point equals either $W - L$ in the states (1) and (2) in which a loss occurs or W in the states (3) and (4) in which no loss occurs. Therefore, if the subject does not demand the insurance, there is neither a

⁸For the sake of simplicity, we assume that the diminishing marginal sensitivity for gains and losses are equal, i.e., $\alpha \approx \beta$. This assumption is supported by Tversky and Kahneman (1992) who find a median value of $\alpha_m = \beta_m = 0.88$.

⁹For a further discussion on this issue see Schmidt (2016).

¹⁰PT as proposed by Kahneman and Tversky (1979) assumes that the reference point is a fixed value. Accordingly, our model is actually embedded in the so-called Third-generation PT which is proposed by Schmidt, Starmer, and Sugden (2008) and allows endogenous and state dependent reference points.

gain nor a loss in all four states. If the farmer demands the insurance, there is a gain of $-pI + I$ if the insurance pays out (state (1) and (3)). Furthermore, there is a loss of the insurance premium pI if the insurance does not pay out (state (2) and (4)). Table 1.3 presents a summary of the encoded outcomes and their probabilities.

State	Loss		No Loss	
	Indemnity (1)	No Indemnity (2)	Indemnity (3)	No Indemnity (4)
Probability	$p(1 - q_1)$	r	r	$(1 - p)(1 - q_2)$
Gains/Losses, No Insurance	0	0	0	0
Gains/Losses, Index Insurance	$(1 - p)I$	$-pI$	$(1 - p)I$	$-pI$

Notes: The table shows encoded outcomes for the reference point no insurance coverage.

Table 1.3: No insurance coverage as reference point

A farmer demands the insurance if the PT Value of demanding is at least as large as the PT Value of not demanding. Neglecting probability weighting, the condition that needs to be fulfilled equals¹¹

$$-\lambda(1 - p)(pI)^\alpha + p((1 - p)I)^\alpha \geq 0. \quad (1.2)$$

From condition (1.2) we can observe that an increase in the loss aversion coefficient λ negatively impacts the likelihood to demand the index insurance. Furthermore, the basis risk probability r is not included in the condition. Hence, a possible in- or decrease in basis risk does not impact the insurance demand decision. Both predictions hold independently of the value of α and, thus, under risk neutrality, i.e., $\alpha = 1$, as well as under risk aversion, i.e., $\alpha < 1$. The following proposition summarizes these predictions.

Proposition 1.2.1. *Given the reference point 'No Insurance Coverage', insurance demand is independent of basis risk and decreasing with loss aversion.*

Rearranging of inequality (1.2) shows that a farmer only demands the insurance, if

$$\lambda \leq \left(\frac{p}{1 - p} \right)^{1-\alpha}.$$

¹¹Within our model set up we assume that the probability of upside and downside basis risk are the same. Therefore $p(1 - q_1) + r = p(1 - q_1) + pq_1 = p$. Similarly $r + (1 - p)(1 - q_2) = 1 - p$.

Accordingly, as also stated by Gottlieb and Mitchell (2020), scenarios in which the probability that a loss occurs is smaller than 0.5, i.e., $p < 0.5$, require the loss aversion parameter to be smaller than 1, i.e., $\lambda < 1$. This implies that losses do not loom larger than gains and therefore contradicts one of the most tested assumptions of PT. Furthermore, using the median PT parameter $\alpha_m = 0.88$ and $\lambda_m = 2.25$ shows that a loss probability of $p > 0.99$ is required such that a farmer demands the insurance.¹² Thus, it is very likely that farmers using the reference point 'No Insurance Coverage' never demand an actuarially fair priced insurance.¹³ We further analyze insurance demand if the premium is lower than its actuarially fair value. We denote $s > 0$ as the subsidy factor and assume that $\Pi = (1 - s)pI$ holds. Proposition 1.2.2 states subsidy requirements.

Proposition 1.2.2 (Requirement for the subsidy). *A farmer with reference point 'No Insurance Coverage' demands the subsidized insurance only if the inequality*

$$s \geq 1 - \frac{1}{p \left(\left(\lambda^{\frac{1-p}{p}} \right)^{\frac{1}{\alpha}} + 1 \right)}$$

is fulfilled. The subsidy requirement is increasing with loss aversion.

Proof: Appendix 3.7.

Using the median PT parameters $\alpha_m = 0.88$, $\lambda_m = 2.25$ and assuming that the loss probability lies between 5% and 50%, i.e. $0.05 < p < 0.5$, Proposition 1.2.2 predicts that a subsidy between 55% and 85% is required such that a farmer with reference point 'No Insurance Coverage' demands the insurance.

1.2.2 Perfect Insurance Coverage

We now analyze insurance demand with a state-dependent reference point equal to wealth with full coverage of an insurance that always - and only - pays out in case of a loss. Under full coverage the indemnity payment equals the loss (i.e., $I = L$). Accordingly, the

¹²The median values $\alpha_m = 0.88, \lambda_m = 2.25$ of Kahneman and Tversky (1979) were estimated in experiments with a small number of students. These populations are among the least representative on a lot of dimensions (Henrich, Heine, and Norenzayan, 2010). However, using PT parameters estimated by Liu (2013) and Holden and Quiggin (2017) in a closer context lead to similar strict conditions.

¹³This implication is straightforward since the farmer regards the insurance as an investment and the decision to demand the insurance as being independent of crop risk. Hence, he does not demand a zero expected return, positive risk insurance contract.

reference point is $W - pI$ in all four states.¹⁴ Therefore, if the farmer does not demand the insurance and a loss occurs (state (1) and (2)), there is a loss of $I - pI$. Furthermore, there is a gain of the premium pI if no loss occurs (state (3) and (4)). If the farmer demands the insurance, the existence of basis risk leads to a loss of the indemnity payment I in state (2) and a gain of I in state (3). Both states occur with the same probability r . Table 1.4 presents a summary of the encoded outcomes and their probabilities.

State	Loss		No Loss	
	Indemnity (1)	No Indemnity (2)	Indemnity (3)	No Indemnity (4)
Probability	$p(1 - q_1)$	r	r	$(1 - p)(1 - q_2)$
Gains/Losses, No Insurance	$(p - 1)I$	$(p - 1)I$	pI	pI
Gains/Losses, Index Insurance	0	$-I$	I	0

Notes: The table shows encoded outcomes for the reference point perfect insurance coverage.

Table 1.4: Perfect insurance as reference point

A farmer demands the insurance if the PT Value of demanding is at least as large as the PT Value of not demanding. Neglecting probability weighting, the condition that needs to be fulfilled is

$$r(1 - \lambda)I^\alpha > -p\lambda((1 - p)I)^\alpha + (1 - p)(pI)^\alpha. \quad (1.3)$$

From condition (1.3) we can see that an increase in the basis risk probability r negatively impacts the likelihood to demand the index insurance. Furthermore, rearranging leads to

$$\lambda(p(1 - p)^\alpha - r) + r - (1 - p)p^\alpha > 0.$$

Thus, the likelihood to demand the insurance is increasing with loss aversion exactly if $p(1 - p)^\alpha > r$. An increase in the basis risk probability r makes it less likely that this condition is fulfilled. Recalling from our model set up described at the beginning of Section 1.2, $r = pq_1$ holds, where q_1 denotes the probability that, given a loss, the insurance does not pay out. Hence, the condition simplifies to $(1 - p)^\alpha > q_1$. The left side of the inequality is decreasing with α . Thus, it is sufficient to analyze the case $\alpha = 1$.

¹⁴In the states (1) and (2) in which a loss occurs the reference point is $W - pI - L + I = W - pI$. In the states (3) and (4) in which no loss occurs farmers do not receive any indemnity payment but still have to pay the insurance premium pI . Thus, the reference point is also $W - pI$.

Assuming that the loss probability p is below 50%, this condition is fulfilled as long as $q_1 < 0.5$. We believe that an insurance with a non-performance probability of above 50% is an unlikely scenario. Accordingly, we conclude that the likelihood to demand the insurance is increasing with loss aversion under risk neutrality, i.e., $\alpha = 1$, and, therefore, also under risk aversion, i.e., $\alpha < 1$. Proposition 1.2.3 summarizes the predictions.

Proposition 1.2.3. *Given the reference point 'Perfect Insurance Coverage', insurance demand is decreasing with basis risk and increasing with loss aversion. Furthermore, the positive impact of loss aversion diminishes with an increasing basis risk.*

1.2.3 Model Predictions

Our behavioral model contrasts insurance demand for two reference points: 'No Insurance Coverage' and 'Perfect Insurance Coverage'. We believe that these reference points are likely to be related to farmers' level of insurance understanding and, therefore, the awareness of the loss-hedging benefit that insurance provides. A farmer without further understanding of the insurance is not aware of the loss-hedging benefit. Instead, he regards the insurance as an investment whose payout is not related to harvest loss. Consequently, the farmer only evaluates a payout larger than the purchase price of the investment - i.e., the insurance premium - as a gain. This view of 'insurance as investment' rather than a loss-hedging device is supported by Patt et al. (2009), who report that some farmers are upset if the indemnity payment is less than the premium paid for the insurance. A farmer with further insurance understanding, however, is aware of the loss-hedging benefit. Accordingly, he regards the insurance as a loss-hedging device and exclusively expects an indemnity payment in case of harvest loss. The analyzed reference points capture these two scenarios. We, therefore, suggest that the reference point 'No Insurance Coverage' models the index insurance demand decision of a farmer who is unaware of the loss-hedging benefit that insurance provides, whereas the reference point 'Perfect Insurance Coverage' models the index insurance demand decision of a farmer who is aware of the loss-hedging benefit that insurance provides. We refer to these two types as naive and insurance-literate farmers.

We can relate our interpretation of the reference points to models that endogenize expectations as the reference point (Kőszegi and Rabin, 2006, 2007; Gottlieb and Mitchell, 2020). These models suggest that if a farmer plans to be covered by an insurance, wealth

under insurance coverage serves as the reference point. Farmers who are unaware of the loss-hedging benefit of insurance do most likely not plan to buy the insurance. Accordingly, their reference point should always be the status quo ('No Insurance Coverage'). Among the group of farmers that are aware of the loss-hedging benefit at least the ones with a sufficiently large aversion towards losses (risks) plan to be covered by an insurance that would, in the ideal case, pay out an indemnity whenever a loss occurs. Hence, 'Perfect Insurance Coverage' serves as the reference point for these farmers. We can further relate our interpretation of the reference points to recent work by Schmidt (2016). Several empirical studies suggest that individuals often use risk-free outcomes as the reference point. Transferring this to the insurance context, Schmidt (2016) proposes wealth under full insurance coverage as a reference point. However, if farmers are unaware of the loss-hedging benefit that insurance provides, they do not anticipate that full coverage of an insurance should imply a risk-free outcome. Thus, following the argumentation of Schmidt (2016), only the farmers that are aware of the loss-hedging benefit should use the reference point 'Perfect Insurance Coverage'.

Table 1.5 summarizes the predictions of our behavioral model and compares them to empirical findings from the literature. Columns (1) and (2) display the predictions, Columns (3) and (4) the empirical findings.

	Behavioral Model		Empirical Findings	
	naive (1)	Insurance-literate (2)	naive (3)	Insurance-literate (4)
Basis risk	0	—	0	—
Loss aversion	—	+	n.a.	n.a.

Notes: The table summarizes predictions and empirical findings.

Table 1.5: Behavioral insurance demand model and empirical findings

Following our PT model, basis risk is not related to the insurance demand of a naive farmer, whereas it negatively impacts the insurance demand of an insurance-literate farmer. A recent study by Jensen, Mude, and Barrett (2018) supports this prediction. Their results suggest that further understanding of the product considerably increases sensitivity to basis risk. Jensen, Mude, and Barrett (2018) further find only very little relationship between basis risk and insurance demand among farmers that were not further educated about the index insurance. Our second prediction addresses the effect of loss aversion on index insurance demand. To the best of our knowledge, no research on

the relationship between loss aversion and index insurance demand exists. We, therefore, state our core Hypothesis 1.2.1:

Hypothesis 1.2.1. *The impact of loss aversion on index insurance demand varies with the level of insurance understanding. While insurance demand is decreasing with loss aversion among farmers who are unaware of the loss-hedging benefit that insurance provides, it is increasing with loss aversion among farmers who are aware of the loss-hedging benefit that insurance provides.*

1.3 Empirical Support

1.3.1 Assumptions

To identify the causal relationship between insurance understanding and the effect of loss aversion on index insurance demand, strict assumptions must be met. Understanding should be randomly distributed across a group of otherwise similar farmers. Furthermore, an identical insurance contract should be offered to all farmers at the same point in time. Finally, farmers should participate in choice tasks eliciting loss aversion. We did not conduct our own field experiment. Instead, we make use of the publicly available dataset of the randomized controlled trial (RCT) conducted by Cole et al. (2013) to provide empirical support for our core hypothesis.

Cole et al.'s (2013) field experiments featured real world index insurance take-up decisions for a relevant and representative subject pool. Next to these advantages the set up imposes one major limitation; Cole et al. (2013) did not elicit parameters for loss aversion. We need to impose strict assumptions to interpret farmers' choices in an experimental gamble as indicators of loss aversion. Farmers were asked to choose among lotteries varying in risk and expected return. Following Binswanger (1981), Cole et al. (2013) interpret lottery choices as indicators of risk aversion. As we discuss in Section 1.3.3, the payouts of the experimental choice task are small relative to farmers' real world income. Thus, lottery choices are not necessarily suitable to elicit risk attitudes (Rabin, 2000). Imposing strict assumptions, we show that lottery choices could also be interpreted as indicators of loss aversion. One might be critical of using lottery choices in Binswanger (1981) choice tasks as indicator of loss aversion. Accordingly, we are cautious to interpret any of our results in a causal manner but, instead, view this approach as a first step

to test our core hypothesis. If we gave up our strict assumptions and interpret lottery choices as indicators of risk aversion, our empirical findings would suggest that insurance understanding mitigates the negative effect of risk aversion on index insurance demand. We explain how such a finding can be related to our model in the discussion section of this paper.

In the RCT of Cole et al. (2013), some members of a large group of farmers were randomly assigned to an insurance education module. We split farmers into two groups according to the assignment of the module. We then analyze if the relationship between loss aversion and index insurance demand varies systematically between these two groups. Succinctly put, we use the assignment of the insurance education module as a proxy for a higher likelihood that a randomly drawn farmer is aware of the loss-hedging benefit of insurance. Interpreting the results of this approach as empirical support for our core hypothesis imposes two key assumptions that deserve to be explained in detail. First, the insurance education treatment has an overall positive effect on farmers' awareness of the loss-hedging benefit that insurance provides (A1).¹⁵ Second, the insurance education treatment does not impact the relationship between loss aversion and insurance demand other than by affecting farmers' awareness of the loss-hedging benefit that insurance provides (A2).

An ideal experiment would require that every farmer is initially unaware of the loss-hedging benefit of insurance and every farmer in the treatment group becomes (due to the education module) aware of the loss-hedging benefit. Each requirement by itself and, particularly, the overlap of both is unlikely to be met in the field. Nevertheless, assumption A1 ensures that the share of farmers that are aware of the loss-hedging benefit is larger in the treatment than in the control group.¹⁶ Accordingly, any differences in outcome variables between the two groups can possibly be attributed to differences in the awareness of the loss-hedging benefit that insurance provides. The same holds for differences in the effect of covariates on outcome variables. However, the insurance education treatment might also impact factors other than awareness of the loss-hedging benefit. The concern is whether we are measuring the true effect of awareness or whether the findings could be driven by other factors, such as the education module causing an increase in the per-

¹⁵This assumption implicitly requires that a sufficiently large number of farmers is unaware of the loss-hedging benefit before the RCT takes place.

¹⁶This implication requires that the initial share is similar in the control and treatment group. An assumption that is met due to random treatment assignment.

ceived riskiness of farming. To exclusively attribute systematic differences in the effect of loss aversion on insurance demand to differences in awareness of the loss-hedging benefit, assumption A2 must be met. Finally, it is unlikely that every single farmer in the control group is unaware and every single farmer in the treatment group becomes (due to the education module) aware of the loss-hedging benefit of insurance. Thus, an identification based on the random assignment of an insurance education treatment works against us, making us less likely to find statistically significant effects. Accordingly, our analysis most likely provides an underestimate of the true effect of insurance understanding on the relationship between loss aversion and index insurance demand. In the following section, we briefly introduce the RCT of Cole et al. (2013) and discuss the assumptions A1 and A2 for this specific set up.

1.3.2 Design

In 2006, Cole et al. (2013) conducted different experiments in two rural regions of India, Andhra Pradesh and Gujarat. The setting related to our hypothesis is the one in Andhra Pradesh. Out of an entire sample population of 1,053 farmers in this region, Cole et al. (2013) randomly selected 700. These farmers were visited by trained research institute employees and received a small monetary compensation for welcoming the employee; they were further able to buy the insurance policy on the spot. For information regarding contract details we refer to Cole et al. (2013). The authors randomized the content of the visits independently along three dimensions. First, locally trusted people endorsed the employee prior to visits. Second, some farmers received an additional high reward at the time of the visit. Third, and most interesting for us, some farmers received further education about the product.¹⁷ From now on, we refer to these three treatments as Endorsement, High Reward, and Insurance Education. Table 3.18 in the Appendix provides an overview of group sizes in the different treatments. Additionally, Cole et al. (2013) used surveys to record basic demographic characteristics, risk attitudes and, farmers' decisions on whether to demand insurance. Table 3.19 in the Appendix provides summary statistics.

Utilizing the Insurance Education treatment for a test of our core hypothesis requires

¹⁷Cole et al. (2013) use the treatments to investigate the effect of first, trust, second, liquidity constraints and third, insurance understanding on insurance demand. Our work replicates the third investigation, but with PT preferences, i.e., by introducing the behavioral bias loss aversion.

that assumptions A1 and A2 are met. Cole et al. (2013) show that a significant portion of these farmers cannot answer simple financial questions. They further show that the understanding of the core component of the index insurance is low. The insurance pays out an indemnity if the rainfall measured at the closest weather station falls below a certain threshold. The possible payout is set in millimeters of rainfall. However, less than one-quarter of the sample population is familiar with this unit of measurement.¹⁸ Accordingly, the majority of farmers cannot relate insurance payouts to harvest losses. Thus, farmers have only limited understanding of the loss-hedging benefit of the insurance.¹⁹ The Insurance Education treatment was designed in cooperation with the local agricultural university to specifically address this issue. Thus, in-line with Cole et al.'s (2013) interpretation of the treatment, we conclude that it positively affected the overall understanding of the insurance and, particularly, the awareness of the loss-hedging benefit that insurance provides. Accordingly, assumption A1 is met.

A first concern regarding assumption A2 is that the insurance education module could increase the perceived riskiness of farming. However, the literature agrees that the local population is, independent of any treatments, aware of the riskiness of farming (Giné, Townsend, and Vickery, 2008; Hazell and Hess, 2010; Fisher and Snapp, 2014). Furthermore, it is unlikely that an insurance education module in which farmers learn how millimeters of rainfall translate into depth of soil moisture in the ground is related to the perceived riskiness of farming. A second concern is that the insurance education module could increase trust in the provider. In this case, farmers assigned to the Insurance Education treatment might perceive any product offered during the visit as less risky. It is unlikely that the content of the education module affects trust in the provider. Thus, the only way the Insurance Education treatment could increase trust in the provider would be through personal interaction during the treatment. However, every visited farmer (700 of 1,053) interacted with a research institute employee. To assuage the concern that our results are driven by trust in the provider rather than by awareness of the loss-hedging benefit that insurance provides, we conduct a separate analysis that only includes visited farmers. This approach can be found as a robustness check in a later section of the paper.

¹⁸According to Cole et al. (2013), the most common measure used in farming in this specific region is depth of soil moisture in the ground. Only 22% of the sample population understand how millimeters of rain translate into depth of soil moisture.

¹⁹The authors conclude that their set up 'provides prima facie evidence that households have only limited understanding of the product' (Cole et al., 2013, p. 16).

Furthermore, Cole et al. (2013) conducted the first treatment (Endorsement) to explicitly investigate the impact of trust in the provider. Thus, if trust in the provider would be of importance for the relationship between loss aversion and insurance demand, we should observe systematic differences in the effect of loss aversion for those who did receive the Endorsement treatment and those who did not. As we show in the empirical analysis, this is not the case.

1.3.3 Specification

Cole et al. (2013) did not elicit loss and risk aversion parameters simultaneously.²⁰ Instead, within their experiments, each farmer only had to choose one of the six Binswanger (1981) lotteries listed in the first three columns of Table 1.6. The payoff of any of these lotteries was determined by the toss of a fair coin.

(1) Lottery	(2) Heads	(3) Tails	(4) $\mathbb{E}[\text{Payoff}]$	(5) Share	(6) Loss (Heads)	(7) Gain (Tails)	(8) $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$	(9) λ_{main}
(1)	25	25	25	10.3%	0	0	$7 \leq \lambda$	8.5
(2)	20	60	40	25.6%	5	35	$4 \leq \lambda \leq 7$	5.5
(3)	15	80	47.5	18.0%	10	55	$3 \leq \lambda \leq 4$	3.5
(4)	10	95	52.5	25.3%	15	70	$2 \leq \lambda \leq 3$	2.5
(5)	5	105	55	11.0%	20	80	$1 \leq \lambda \leq 2$	1.5
(6)	0	110	55	9.9%	25	85	$\lambda \leq 1$	1

Notes: The table shows outcomes of the lotteries and the share of people who choose these lotteries.

Table 1.6: Binswanger lotteries

Following Binswanger (1981), Cole et al. (2013) interpret farmers' choices as indicators of risk aversion. The payoffs of the choice task range between Rs. 0 – 110 whereas farmers' mean yearly income is Rs. 57,991 and farmers' median yearly income is Rs. 34,116.²¹ Thus, the payouts of the experimental choice task are small relative to farmers' real world income.²² Accordingly, lottery choices only reflect risk aversion if farmers are assumed to evaluate the possible experimental income in isolation from their lifetime income (Rabin, 2000). This assumption is not necessarily met (for a discussion we refer to

²⁰Simultaneous elicitation of loss and risk aversion parameters is proposed by Tanaka, Camerer, and Nguyen (2010) and, for example, used by Liu (2013) in a different agricultural context.

²¹The differences between mean and median are driven by significant income differences between agricultural laborers and skilled, respectively landed farmers (Cole et al., 2013). Given these values, the maximum income from the choice task amounts to 2.3% ($= 12 \cdot 110/57,991$) of the average monthly income. Hence, stakes are much smaller than in the high-stake decision task of Binswanger (1981) with stakes amounting to a month's average income.

²²We thank an anonymous referee for suggesting a comparison between the experimental income and farmers' real worlds income.

Harrison, List, and Towe, 2007; Heinemann, 2008). Following other experimental studies (Fehr and Goette, 2007; Gächter, Johnson, and Herrmann, 2007; Karle, Kirchsteiger, and Peitz, 2015; Beshears et al., 2017), we assume that farmers integrate the potential income from the choice task with their lifetime income. According to Rabin’s (2000) calibration theorem, this essentially implies that farmers must be risk neutral for low-stake gambles. The intuition for this is, as Fehr and Goette (2007) explain, that risk averse behavior for low-stake gambles would imply absurd degrees of risk aversion in medium- and high-stake gambles.

Under Expected Utility, risk neutrality implies that farmers should choose the lotteries with the largest expected payoffs (Lottery (5) or Lottery (6); see Column (4) of Table 1.6). If we observe lottery choices that are not consistent with this predictions, then this might indicate loss aversion (Fehr and Goette, 2007; Gächter, Johnson, and Herrmann, 2007). Only 20.9% ($= 11.0\% + 9.9\%$) of the sample population choose the lotteries with the largest expected payoff (see Column (5) of Table 1.6). 10.3% even choose Lottery (1), the lottery with the lowest expected payoff.

In the Binswanger (1981) choice set, Lottery (1) is risk-free. Harrison and Rutström (2008) argue that this certain amount may provide a natural reference point for subjects to identify gains and losses, which, in turn, might frame choices in a manner that is sign dependent.²³ We follow this argument and contemplate the possibility that farmers’ choices indicate loss aversion. Accordingly, we encode all possible lottery outcomes as either gains or losses with respect to the reference point of the certain amount of 25. For instance, an outcome of 20 in Lottery (2) is encoded to a loss of 5 ($= 20 - 25$). Losses and gains are displayed in Column (6) and (7) of Table 1.6.

Similar to the procedure of Gächter, Johnson, and Herrmann (2007) and Fehr and Goette (2007), we can then determine loss aversion in the risky choice task by applying PT. Neglecting probability weighting and assuming risk neutrality, the PT Value of Lottery (i) is given by $V_i = 0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i$, where G_i and L_i denote the gain and the

²³This argument is supported by empirical findings showing that subjects faced with a choice task do not use the status quo as the reference point, but, instead use the risk-free option and evaluate the outcomes of the other options relative to this reference point (Hershey and Schoemaker, 1985; Robinson, Loomes, and Jones-Lee, 2001; Bleichrodt, Pinto, and Wakker, 2001).

loss associated with Lottery (i); and λ denotes the parameter of loss aversion.²⁴ A farmer chooses Lottery (i) if its PT Value V_i is at least as large as the PT Value of the five other lotteries. Thus, $V_i \geq V_j \forall j \neq i$ has to hold. Inserting the PT Value and rearranging leads to $0.5 \cdot (G_i - G_j) \geq \lambda \cdot 0.5 \cdot (L_i - L_j) \forall j \neq i$. In Part 3.7 of the Appendix, we show that these conditions impose a lower and upper bound for the loss aversion parameter. The bounds depend on the possible gains and losses associated with Lottery (i) and its two neighboring Lotteries ($i - 1$) and ($i + 1$). Farmers' choices of Lottery (i) require a loss aversion parameter λ such that $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$ holds. The first and last lottery only have one neighboring lottery. Thus, we can only derive one interval bound. Column (8) of Table 1.6 displays the parameter intervals associated with farmers' choices in the Binswanger (1981) choice task.²⁵

As the loss aversion parameter cannot be uniquely inferred, we impose the following values for the main regression analysis (see Column (9) of Table 1.6). For Lottery (2) to Lottery (5), we use intervals' midpoints. For Lottery (6), we impose the value $\lambda = 1$ to ensure that subjects are not assumed to be loss-seeking.²⁶ Regarding Lottery (1), we note that the distances between our imposed values and the lower interval bounds are 1.5 ($= 5.5 - 4$) for Lottery (2), and 0.5 for Lotteries (3), (4) and (5). The distance can not be calculated for Lottery (6). However, arguing that farmers are unlikely to be loss seeking, the lower bound would be 1 which would imply that the distance is 0. The sequence of distances is weakly decreasing. To ensure that Lottery (1) fits into this sequence, we impose the value $\lambda = 8.5$ ($= 7$ (lower bound) + 1.5 (maximum distance)). Using these values, the mean loss aversion parameter is $\lambda = 3.8$ and the median is $\lambda = 3.5$. In line with

²⁴We neglect probability weighting to ensure that the assumptions imposed to derive the loss aversion measure coincide with the assumptions of the model section. As we show in Part 3.7 of the Appendix, the assumption can be relaxed and it is sufficient to assume that subjects weight a 0.5-chance for gaining or losing equally ($\pi^+(0.5) = \pi^-(0.5)$). This assumption is, for instance, fulfilled by the probability weighting function proposed by Prelec et al. (1998).

²⁵Deriving the measure of loss aversion, we assume that farmers are risk neutral for low-stake gambles. In contrast to the income from the experimental gamble, the income from farming as well as the size of possible losses due to droughts is large (Cole, Giné, and Vickery, 2017; Jayachandran, 2006). Thus, the decision to insure can be regarded as a high-stake decision. Accordingly, assuming that farmers are risk neutral for low-stake gambles does not necessarily imply that farmers are risk neutral when making the insurance purchase decision. Our predictions addressing the impact of loss aversion on index insurance demand hold under risk neutrality, i.e., $\alpha = 1$, as well as under risk aversion, i.e., $\alpha \leq 1$. Thus, even if one would argue that our assumption should imply risk-neutrality for the insurance demand decision our model predictions would remain unchanged.

²⁶According to our loss aversion measure, a small share of the sample is not loss averse (Lottery (6); 9.9%). This observation is in line with other studies eliciting PT preferences (Gächter, Johnson, and Herrmann, 2007; Liu, 2013).

PT preferences estimated in other developing countries (Liu, 2013; Holden and Quiggin, 2017), this value is larger than the one estimated by Kahneman and Tversky (1979) in student experiments. As we discuss in the robustness section, the regression results are not driven by these specific parameter choices but are robust to several redefinitions.²⁷

Our main analysis closely follows the empirical strategy of Cole et al. (2013). Each household is one observation. Cole et al. (2013) only report choices within the Binswanger (1981) lotteries for 941 out of 1,053 farmers. Thus, the sample size reduces from 1,053 to 941. Because the assignment of the three treatments is random, the empirical specification is straightforward.²⁸ For the entire sample we estimate a linear probability model of household insurance demand as a function of the treatment variables and household level controls. In contrast to Cole et al. (2013), our main interest is the link between loss aversion and insurance demand across groups with varying levels of insurance understanding. Accordingly, we add an interaction term of loss aversion with the binary indicator for participation in the randomized Insurance Education treatment. Finally, we include interaction terms of loss aversion with dummy variables for the other two treatments and village fixed effects to control for multiple treatment effects and unobserved village specific characteristics. Hence, our model to be estimated equals:

$$Y_{i,v} = \alpha \cdot \lambda_i + \beta_1 \cdot V_i + \beta_2 \cdot T_{1,i} + \beta_3 \cdot T_{2,i} + \beta_4 \cdot T_{3,i} + \beta_5 \cdot \lambda_i \times T_{1,i} + \beta_6 \cdot \lambda_i \times T_{2,i} + \gamma \cdot \lambda_i \times T_{3,i} + \beta_X \cdot X_i + f_v + \varepsilon_i. \quad (1.4)$$

As in Cole et al. (2013), our dependent variable Y is a dummy that is one, if farmer i in village v demands at least one insurance contract. Loss aversion is depicted by λ . V is a dummy variable indicating whether visits took place. T_1 , T_2 and T_3 are dummy variables for the Endorsement, High Reward and Insurance Education treatments. X equals a

²⁷In one of the robustness checks, for example, we follow the procedure of Gächter, Johnson, and Herrmann (2007) and impose upper interval bounds. However, lottery choices do not imply an upper bound for Lottery (1). Thus, we still need to impose one additional value.

²⁸To test the successful randomization of the Insurance Education treatment, Table 3.19 in the Appendix presents summary statistics for the whole sample and two subsamples created based on the dummy variable for the Insurance Education treatment. T-tests of covariate means do not invalidate the assumption of random treatment allocation.

vector of the same household level controls as used by Cole et al. (2013).²⁹ Finally, f_v denotes village fixed effects. A negative estimate of α and a positive estimate of γ with a magnitude larger than α would provide empirical support for our core Hypothesis 1.2.1.

1.3.4 Results

Table 1.7 presents take-up rates of different loss aversion cohorts in the subsamples of farmers who did not (No Education) and who did receive the Insurance Education treatment (Education).

	Loss aversion	≤ 1	1-2	2-3	3-4	4-7	≥ 7
No Education	Take-up rate	43.1%	33.8%	22.87%	20%	18.18%	17.39%
	Observations	58	71	153	110	165	69
Education	Take-up rate	40%	43.75%	47.06%	42.37%	44.73%	32.14%
	Observations	35	32	85	59	76	28

Notes: The table shows insurance take-up rates by loss aversion cohorts.

Table 1.7: Take-up rates of different loss aversion cohorts

Among the farmers who did not receive the Insurance Education treatment, loss aversion seems to be negatively related to the take-up rate. Among the farmers who did receive the Insurance Education treatment, the negative relationship vanishes.

Table 1.8 presents our regression results.³⁰ Within the different specifications, we sequentially add further variables. In Specification (1), we regress insurance demand only on a dummy variable for visits, the three treatment dummies and the loss aversion parameter. Specification (2) adds village fixed effects. In Specification (3), we include the interaction term of loss aversion with the Insurance Education treatment dummy. Specification (4) further adds household level controls. Finally, by additionally including interaction terms between loss aversion and the other two treatment dummies, Specifica-

²⁹These are: percentage of cultivated land that is irrigated; above average expected monsoon rain (normalized); whether the household demanded weather insurance in 2004; insurance skills (normalized); whether the household has other insurance; whether the household does not know the provider BASIX; whether the household belongs to a water user group (either a borowell users association or water user group); the number of community groups that the household belongs to and indicator variables for whether the household belongs to a scheduled caste/tribe; whether the household is muslim; gender, log household age and log household size; dummy for secondary education status; interaction whether endorsements occurred in the village and whether the individual household was visited, to identify local spillovers from endorsement.

³⁰Table 1.8 simplifies the regression concentrating on treatments, loss aversion and interaction terms. The complete regression output is presented in Table 3.20 of the Appendix. In the estimated OLS regressions, we use the loss aversion parameters displayed in Column (9) of Table 1.6.

tion (5) represents our main model equation (1.4).

<i>Dependent variable: Insurance Take-Up</i>					
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.012** (0.006)	−0.007 (0.006)	−0.016** (0.007)	−0.012* (0.007)	−0.016** (0.008)
Loss Aversion × Insurance Education (1 =Yes)			0.029** (0.012)	0.029** (0.012)	0.026** (0.012)
Visit (1 =Yes)	0.193*** (0.036)	0.192*** (0.035)	0.190*** (0.035)	0.146*** (0.050)	0.146*** (0.050)
Endorsement (1 =Yes)	0.060* (0.033)	0.080** (0.035)	0.078** (0.035)	0.060 (0.036)	0.113* (0.063)
High Reward (1 =Yes)	0.381*** (0.031)	0.376*** (0.031)	0.381*** (0.031)	0.375*** (0.031)	0.269*** (0.056)
Insurance Education (1 =Yes)	−0.006 (0.031)	−0.011 (0.030)	−0.117** (0.054)	−0.113** (0.054)	−0.099* (0.055)
Loss Aversion × Endorsement (1 =Yes)					−0.013 (0.014)
Loss Aversion × High Reward (1 =Yes)					0.029** (0.013)
Constant	0.090*** (0.032)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Household Controls	No	No	No	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.280	0.356	0.360	0.387	0.391
Adjusted R ²	0.276	0.327	0.330	0.347	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses.

Table 1.8: Determinants of insurance demand

Across all five specifications, the coefficients of the Visit dummy and the dummies for the treatments High Reward and Endorsement are qualitatively and quantitatively similar to the results of Cole et al. (2013).³¹ Furthermore, the coefficient of loss aversion is negative and significant in Specification (1). The effect vanishes after adding village fixed effects in Specification (2). When interacting the loss aversion parameter with the dummy for the Insurance Education treatment in Specifications (3) and (4), where the latter controls for farmer characteristics, we estimate a significant negative effect of loss aversion and a significant positive effect of its interaction with the Insurance Education

³¹Being assigned to a household visit alone increases insurance demand by 14.6 percentage points in specification (5) to 19.3 percentage points in Specification (1). A high reward increases insurance demand by 26.9 percentage points in Specification (5) to 38.1 percentage points in Specification (3). The effect of the Endorsement treatment varies between 6.0 percentage points in Specification (1) and 11.3 percentage points in Specification (5).

treatment dummy. More precisely, given an increase in loss aversion by one standard deviation ($sd = 2.195$, see Table 3.19) the likelihood to demand at least one insurance contract decreases by 2.6 ($= 2.195 \times -0.012$) percentage points in Specification (4) to 3.5 ($= 2.195 \times -0.016$) percentage points in Specification (3). However, for farmers assigned to the Insurance Education treatment, the same change results in an increase by 2.9 ($= 2.195 \times (-0.016+0.029)$) percentage points in Specification (3) to 3.7 ($= 2.195 \times (-0.012+0.029)$) percentage points in Specification (4). The effects remain stable if we add interaction terms of the other two treatment dummies with loss aversion in Specification (5). According to the summary statistics in Table 3.19 of the Appendix, the mean take-up rate is 30.2% within the entire sample, 43.2% within the subsample of farmers who received the Education treatment and 23.6% within the subsample of farmers who did not receive the Education treatment. Thus, the effects have a meaningful magnitude. Hence, the empirical findings support our core Hypothesis 1.2.1.

The empirical analysis further points out two aspects beyond the core hypothesis. First, the findings of Specification (5) suggest that the effect of the High Reward treatment on insurance demand is increasing with loss aversion. Following Cole et al. (2013), the high reward could be regarded as a tool to overcome liquidity constraints. In this sense, the reward is a high subsidy. Accordingly, farmers with a larger aversion towards losses react more sensitively to a high subsidy than the other farmers. This finding provides suggestive evidence for our Proposition 1.2.2 which predicts minimum subsidy requirements for farmers who are unaware of the loss-hedging benefit of insurance to increase with loss aversion.³²

Second, the empirical findings of Specification (3), (4) and (5) suggest that the effect of the Insurance Education treatment is also heterogeneous in loss aversion. In particular, the Insurance Education treatment only positively impacts the insurance demand of farmers with an above median aversion towards losses.³³ There are two potential reso-

³²The interaction term Loss Aversion $\times$ High Reward (1=Yes) is estimated within the entire sample. Thus, for this explanation to hold, the overall awareness of the loss-hedging benefit that insurance provides has to be low. As discussed earlier, this is, indeed, the case. Splitting the sample in farmers who received and who did not receive the Insurance Education treatment, we show that the heterogeneous effect is actually driven by the ones who are, on average, less likely to be aware of the loss-hedging benefit that insurance provides (see Table 3.21 and Table 3.22 in the Appendix).

³³The impact of the Insurance Education treatment is negative for $-0.117 + \lambda \cdot 0.029 < 0$. This is equivalent to $\lambda < 4.0$. In Specification (4) and (5) the impact is negative for loss aversion parameters below 3.9 (0.113/0.029) and 3.8 (0.099/0.026) respectively. The median loss aversion in the sample is 3.5. The observation that the Education treatment does not have an overall positive effect on insurance demand is in-line with the findings of Cole et al. (2013).

lutions for this puzzling finding.³⁴ The first resolution relates to the preferred personal equilibrium approach (Kőszegi and Rabin, 2006, 2007) that endogenizes expectations as the reference point. Consistent with this approach, it could be the case that out of the farmers who received insurance education only the ones with a high aversion towards losses plan to buy it. Thus, these farmers would use the reference point wealth with insurance coverage, whereas the others (farmers with a smaller aversion towards losses) would use the reference point wealth without insurance coverage. The shift in the reference point may, as also suggested in the conclusion of Gottlieb and Mitchell (2020) for a general insurance context, explain the divergence in preferences.³⁵ The second resolution suggests that the empirical finding might reflect a strategic consideration of those receiving insurance education. Farmers learn that they should only buy insurance if their aversion towards losses exceeds a threshold. Accordingly, only the farmers with a high aversion towards losses decide to buy the insurance.³⁶

1.3.5 Robustness

Besley and Case (1993) argue that with cross-sectional data any ex post measures of covariates could be affected by previous adoption decisions and are, therefore, endogenous. Although farmers in our sample make their insurance demand decision at the same time the survey is conducted, previous insurance demand might be regarded as a possible source of endogeneity. We replicate our regressions on a subsample of farmers that did not demand any insurance in the previous period. As presented in Table 3.23 of the Appendix, the same qualitative results as in Table 1.8 are observable.

Our sample includes visited as well as non-visited farmers. We replicate our main analysis on the sample of visited farmers for two different reasons. First, as discussed earlier, one could argue that the personal interaction included in the Insurance Education treatment increases trust in the provider, which, in turn, could impact the relationship

³⁴We thank an anonymous referee for suggesting these two resolutions.

³⁵Gottlieb and Mitchell (2020) suggest that the same subject might have different reference points in different insurance markets. Consistent with the models of (Kőszegi and Rabin, 2006, 2007), they suggest that the shift in reference point could be induced through the effect of framing.

³⁶For this resolution to hold we need to assume that farmers who do not receive insurance education are confused about the product and, therefore, do not follow a systematic buying strategy.

between loss aversion and insurance demand.³⁷ Replicating the main analysis on the sample of visited farmers ensures that every farmer interacted with a research institute employee. Accordingly, the level of trust induced through personal interaction should not vary within the sample. Second, one could argue that although the visited farmers were chosen randomly, this group is not comparable to the group of non-visited farmers. Visited farmers were able to demand the insurance policy on the spot, higher effort was required by the non-visited ones. These farmers could only buy the insurance at local branches. Furthermore, the three treatments were independently randomized among the visited. Thus, multiple treatments were possible. Accordingly, a farmer assigned to the Insurance Education treatment is, by construction of the experiment, more likely to receive a second treatment than a farmer that is not visited. Table 3.24 in the Appendix displays the results of our main empirical analysis on the sample of visited farmers. The estimates and their significance levels remain stable.

According to our main specification, the impact of the Insurance Education treatment as well as the High Reward treatment is increasing with loss aversion. Furthermore, as already discussed, the analyzed setting features multiple treatments. To verify that the estimated joint impact of loss aversion and the Insurance Education treatment is not driven by a spillover effect of the High Reward treatment, we replicate our analysis on the subsample of farmers that did not receive the High Reward treatment. The estimates presented in Table 3.25 of the Appendix are quantitatively similar to the ones of our main regression Table 1.8.

Our measure of loss aversion suggests that farmers' choices in the Binswanger (1981) choice task impose a lower and upper bound for the loss aversion parameter. However, we need to impose fixed values for the regression analysis. The values used for the main analysis are displayed in Column (9) of Table 1.6. Our choice for Lottery (1) might seem particularly arbitrary.³⁸ To overcome the concern that our results are driven by this specific choice, we repeat our main analysis with varying value choices for Lottery (1). We use $\lambda = 7.5$ ($= 7$ (lower bound) $+ 0.5$ (minimum distance between lower bounds and

³⁷In Specification (5) of our main analysis, we do not observe systematic differences in the relationship between loss aversion and insurance demand among farmers who were assigned to Endorsement treatment and farmers who were not. This already suggests that trust is not of major importance for the relationship between loss aversion and insurance demand.

³⁸We used interval midpoints for Lottery (2) to Lottery (5). For Lottery (6) we used the value $\lambda = 1$ to ensure that farmers are not assumed to be loss seeking.

imposed values)) and $\lambda = 7.75$ ($= 7$ (lower bound) $+ 0.75$ (mean distance between lower bounds and imposed values)). As displayed in Tables 3.26 and 3.27 of the Appendix, our estimates and their significance levels remain stable.

We additionally follow the approach of Gächter, Johnson, and Herrmann (2007) and impose upper interval bounds. However, the lottery choices do not imply an upper bound for Lottery (1). We, thus, conduct different analysis with varying value choices for Lottery (1). We use $\lambda = 8$ ($= 7$ (lower bound) $+ 1$ (minimum distance between lower and upper bound)), $\lambda = 8.5$ ($= 7$ (lower bound) $+ 1.5$ (mean distance between lower and upper bound)) and $\lambda = 10$ ($= 7$ (lower bound) $+ 3$ (maximum distance between lower and upper bound)). The estimates presented in Table 3.28, 3.29 and 3.30 of the Appendix are quantitatively similar to the ones of our main regression Table 1.8. We further run one set of regressions in which we use ordinal indicators. We assign the indicators in increasing order meaning that we assign the Lottery (6) whose choice requires the smallest aversion towards losses the indicator 1. The advantage of this method is that we do not need to impose any specific values. As displayed in Table 3.31 of the Appendix, the loss aversion coefficient remains negative and statistically significant and the interaction term positive and statistically significant.

We also replicate Specification (3) to (5) of Table 1.8 without village fixed effects. Again, as presented in Table 3.32 in the Appendix, our findings remain robust.

Finally, regarding the econometric part, estimating a discrete choice model using OLS comes at some costs. We replicate our main analysis using probit regressions. As presented in Table 3.33 of the Appendix, the sign of the estimates are the same as the ones of our main regression and also the significance levels remain stable.

1.4 Discussion

We have made a number of specific modeling choices for the sake of clarity, many of which could be revisited or relaxed. The model is built on the simplifying assumption that farmers gain utility over final wealth. In the appendix, we extend the model by integrating the same two reference points in the intertemporal index insurance demand model of Carter et al. (2014). The extension does not change the model predictions.

Our core model assumption is that the level of insurance understanding is the only

determinant of the reference point. We, therefore, neglect other aspects that might impact the reference point formation, such as salient memories (Schwartzstein, 2014).³⁹ Furthermore, against traditional definition but in line with recent developments (Kőszegi and Rabin, 2006; Schmidt, Starmer, and Sugden, 2008; De Giorgi, 2011; Gottlieb and Mitchell, 2020), farmers' reference points are assumed to be endogenous and state dependent. We suggest that insurance-literate farmers are aware of the loss-hedging benefit of insurance and, therefore, only expect an indemnity payment if a loss occurs. Accordingly, we assume that these farmers use the reference point wealth with coverage of an insurance that pays out and indemnity whenever a loss occurs ('Perfect Insurance Coverage'). With similar reasoning, one could argue that insurance-literate farmers may use the reference point wealth with index insurance coverage. These farmers are also aware of the loss-hedging benefit of insurance. Thus, they do not regard the insurance as an investment. Given the overall benefits of the index insurance, these farmers even accept the rare occurrences in which a harvest loss does not trigger an indemnity payment. Thus, in contrast to the reference point 'Perfect Insurance Coverage', these farmers do not evaluate the downside basis risk scenario as a subjective loss. We analyze the choice of the reference point wealth under index insurance coverage in Part 3.7 of the Appendix. In-line with the predictions for the reference point 'Perfect Insurance Coverage' demand increases with loss aversion.

Our behavioral model analyzes the demand for an insurance that might not pay out in the case of loss but might also pay out in the case of no loss. This is a particular feature of an index insurance. In a broader insurance context, it could be interesting to analyze the impact of loss aversion on the demand for an insurance that might not pay out in the case of loss but never pays out in case of no loss. This is often referred to as contract non-performance (Biener, Landmann, and Santana, 2019). Using the same reference points as in our main model, Part 3.7 in the Appendix shows that in such a scenario the predictions regarding the impact of loss aversion on insurance demand remain unchanged.

We use the dataset of the field experiments conducted by Cole et al. (2013) to test our core hypothesis. The drawback of this approach is that Cole et al. (2013) did not

³⁹Salient memories are of particular interest in the index insurance context because it is very likely to believe that the attitudes towards the insurance of farmers who bought an insurance but suffered from basis risk change dramatically. For a further discussion of reference point formation within financial decision making we refer Baucells, Weber, and Welfens (2011).

elicit parameters for loss aversion. As discussed in detail in Section 1.3.3, we have to impose strict assumptions to interpret choices in the Binswanger (1981) choice task as indicators of loss aversion. Most importantly, we have to assume that farmers integrate the potential experimental income with their lifetime income. Combining this assumption with the observation that the experimental income is relatively small compared to real world income implies that farmers would have to be risk neutral when choosing a lottery (Rabin, 2000). Although the assumption that subjects integrate experimental income with lifetime income is not uncommon (see for example Fehr and Goette, 2007; Gächter, Johnson, and Herrmann, 2007; Dupas and Robinson, 2013; Karle, Kirchsteiger, and Peitz, 2015; Beshears et al., 2017), the implication of risk-neutrality runs counter to the classical interpretation of the Binswanger (1981) choice task. If we give up the assumption that farmers integrate the experimental income with lifetime income and interpret lottery choices as indicators of risk aversion, our empirical findings suggest that insurance understanding mitigates the negative effect of risk aversion on index insurance demand.⁴⁰ The analysis in Part 3.7 of the Appendix shows that index insurance demand is decreasing with risk aversion for the reference point 'No Insurance Coverage' and increasing with risk aversion for the reference point 'Perfect Insurance Coverage'. Accordingly, the empirical findings are also consistent with the predicted relationship between risk aversion and index insurance demand.

We can even derive the same predictions in a model without any reference point. One possibility to set up such a model would be to assume that insurance understanding affects farmers' perception of the correlation between insurances' net transfer and farmers' net loss. Farmers without further understanding of the insurance regard the insurance as a gamble and, therefore, perceive the correlation to be weak, or, in the extreme case, equal to zero (no correlation). According to the model of Clarke (2016), insurance demand would decrease with risk aversion. In contrast, farmers who are aware of the risk-hedging benefit of an insurance perceive the correlation to be strong or, in the extreme case, equal to one (perfect correlation). Given a sufficiently large perceived correlation, insurance demand increases with risk aversion (Clarke, 2016).⁴¹

⁴⁰Cole et al. (2013) map lottery choices into an index between 0 and 1, where large values indicate higher degrees of risk aversion. We have replicated our regressions analysis with these risk aversion parameters. Results are displayed in Table 3.34 of the Appendix.

⁴¹For the case of perfect correlation, classical insurance demand models (Carter et al., 2014; Sarris, 2002) also predict a positive relationship between insurance demand and risk aversion.

In line with our model, we suggest that both, aversion towards risks as well as aversion towards losses, combined with the low level of insurance understanding offer reasonable explanations for the low take-up rates of index insurance products. The empirical set up of Cole et al. (2013) does not allow us to disentangle loss from risk aversion. Accordingly, we can not separate the effect of loss aversion from that of risk aversion. However, we believe that our findings are a relevant and important first support for our core hypothesis.⁴²

1.5 Conclusion and Policy Implications

This paper studies the impact of loss aversion on index insurance demand. We extend existing Prospect Theory insurance demand models (Gottlieb and Mitchell, 2020; Hwang, 2016; Schmidt, 2016) by including basis risk. Choosing two different reference points, we attempt to capture different levels of insurance understanding and, therefore, different levels of awareness of the loss-hedging benefit that insurance provides. According to our model, the impact of loss aversion on index insurance demand is heterogeneous in insurance understanding. The index insurance demand of farmers who are unaware of the loss-hedging benefit of index insurance is predicted to decrease with loss aversion, whereas the effect is the opposite for farmers who are aware of the loss-hedging benefit. Furthermore, our model predicts that farmers who are unaware of the loss-hedging benefit of insurance and have median PT parameters reject an even highly subsidized index insurance offer.

We employ the dataset of Cole et al. (2013) who conducted field experiments in rural regions of India in 2006. In one of three treatments, Cole et al. (2013) randomly assigned insurance education modules to 350 out of 1053 farmers. We use this treatment as an exogenous variation in farmers' level of insurance understanding and, therefore, awareness of the loss-hedging benefit that insurance provides. The experimental setting ensures that both groups were exposed to similar institutions and economic conditions. Furthermore, identical index insurance contracts were offered to all farmers. Our findings support our model conjecture that insurance understanding mitigates the negative effect of loss aversion on index insurance demand. The findings are robust to several model

⁴²Even if one argues that the lotteries can only be used to proxy risk attitudes, the results of Goldstein, Johnson, and Sharpe (2008) who estimate a positive correlation between risk and loss aversion equal to 0.64 support a strong connection between risk and loss attitudes.

specifications that include varying sets of household-level and village-level controls as well as varying methodological approaches. The drawback of this set-up is that Cole et al. (2013) did not elicit loss aversion. We need to impose strict assumptions to interpret lottery choices in the Binswanger (1981) choice task - a task that is usually applied to elicit risk aversion - as indicators of loss aversion. Having said this, our findings could also be read as insurance understanding mitigating the negative effect of risk aversion on index insurance demand. The empirical set up of Cole et al. (2013) does not allow us to separate the effect of loss aversion from that of risk aversion. Accordingly, further experiments need to be conducted to find out if the low index insurance take-up rates are related to a lack of insurance understanding combined with risk aversion, loss aversion or, what we believe is most likely, a combination of risk and loss aversion.

Our analysis provides a case-study for how differences in technology understanding can systematically impact the effect of loss aversion on technology adoption. The results support previous findings on the individual effect of loss aversion (Liu, 2013) and product understanding (Emerick et al., 2016) on technology adoption and extend this literature by analyzing the joint impact of these two factors in a specific scenario.

As droughts are one of the main risks faced by the poor in developing countries, the low adoption rates of formal agricultural insurance have received considerable attention among policy makers in recent years. The theoretical and empirical findings of our study are especially relevant for addressing two puzzles in this context. First, we offer an explanation for the low take-up rates of even highly subsidized insurance: lack of product understanding. According to our model, farmers who are unaware of the loss-hedging benefit of insurance do not even buy a highly subsidized insurance offered at a price equal to 50% of its actuarially fair value. Therefore, as long as farmers do not understand the product, moderately subsidizing the insurance should not be regarded as an effective tool to significantly increase the insurance demand.

Still, investments in insurance education have been made by the public and private sector with many organizations implementing insurance education initiatives on a region-wide scale. Thus, and second, the findings of our study may help to resolve the puzzle why many of these programs were either only partially successful or not successful at all. Our results suggest that policy makers should, in the ideal case, carefully assess individual preferences among their target population before they administer insurance

education initiatives. In our context, for example, educators should be aware that the impact of their modules varies significantly with differences in individuals' loss aversion. Furthermore, the basis risk negatively impacts the insurance demand of farmers who understand the insurance. In this case, the deviation of the indemnity payment from the actual loss needs to be reduced, i.e., the quality of the index insurance needs to be improved. Finally, due to hedonic editing as proposed by PT, the index insurance indemnity payments should become more frequent to increase its attractiveness.

Chapter 2

Demand for Long-term Care Insurance: Time Preferences Matter, Risk Preferences Don't

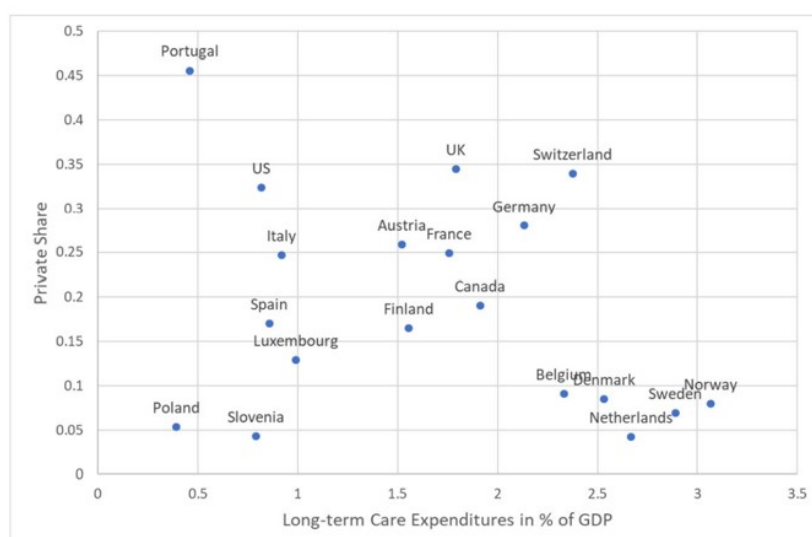
Immanuel Lampe

Abstract

Long-term care (LTC) is one of the largest expenditure risks the elderly in many countries, including the U.S., face. Despite a large private expenditure share, demand for private LTC insurance is low ($< 20\%$). This pre-registered study investigates to what extent attitudes toward uncertainty (risk and ambiguity) and time preferences (impatience) can explain the low demand. Linking three surveys conducted on a sample that is representative of the U.S. population, I find that impatience reduces insurance demand, while attitudes toward uncertainty do not affect demand. The effect of impatience is sizable: on average, impatient subjects are 9 percentage points less likely to demand LTC insurance than their patient counterparts. The effect of impatience increases to 15 - 17 percentage points for subjects with strong risk exposure and subjects who believe that the insurance will actually pay out an indemnity in case of a (valid) claim. The effects of risk aversion and ambiguity aversion are close to 0 and statistically insignificant in all considered samples.

2.1 Introduction

Long-term care (LTC) is one of the largest expenditure risks the elderly in many countries, including the United States (U.S.), face (Brown and Finkelstein, 2011). Between 30 and 50 percent of consumers enter a nursing home at some point of their lives. The average cost for one year in a private room in a nursing home is roughly \$100,000 (Ameriks et al., 2020). Conditional on requiring care, the mean care duration is 2.5 years for women and 1.5 years for men (e.g. Brown and Finkelstein, 2008). Hence, if a consumer needs to enter a nursing home and wishes to stay in a private room, the expected life-time care costs are around \$200,000. This is nearly three times as large as both, the median family income, which was around \$70,000 in 2020 (Shrider et al., 2021), and the median financial wealth at retirement, which was around \$60,000 in 2019 (Survey of Consumer Finances, 2019).



Note: The figure shows total long-term care expenditures as percentage of GDP (on the x-axis) and the private share of these expenditures (on the y-axis) in 2019 for the U.S. and various European OECD countries. The data is taken from OECD (2021).

Figure 2.1: Private Long-Term Care Costs in the OECD.

The private LTC expenditure share in the U.S. is roughly one third. This means that out of every dollar spent on LTC, about 33 cents are financed through private sources. As displayed in Figure 2.1, large LTC expenditures with a sizable private share are not unique to the U.S. they can also be observed for many other OECD countries.

LTC expenses are sizable and unpredictable. Thus there is a case for pooling risks (Brown and Finkelstein, 2007; Muir, 2017; Ameriks et al., 2020). Risk pooling is offered by

private companies in the form of LTC insurance. Despite the large expenditure risk, the demand for private LTC insurance is low. Only between 10 and 20 percent of the elderly in the U.S. are covered by private LTC insurance; the share is similar in other OECD countries (e.g. Ameriks et al., 2016; Braun, Kopecky, and Koreschkova, 2019; Brown, Goda, and McGarry, 2012; Costa-font, Courbage, and Swartz, 2015; Eling, Ghavibazoo, and Hanewald, 2021; Gousia, 2021; Muir, 2017). Recent empirical evidence by Ameriks et al. (2020) highlights that consumers are aware of potentially large LTC costs. Rather than purchasing LTC insurance, however, they tend to self-insure by building up large saving buffers. The avoidance of private LTC insurance products therefore affects saving and consumption decisions throughout the entire lifecycle.

Although consumers are aware of potentially large LTC costs, many struggle to assess both, the likelihood of needing care and the duration for which care is required (e.g. Coe, Skira, and Van Houtven, 2015; Kemper, Komisar, and Alecxih, 2005; Zhou-Richter, Browne, and Gründl, 2010). Hence, consumers face risk and ambiguity when confronted with making a decision about how to prepare for uncertain LTC expenses. While there is mixed empirical evidence on the role of risk aversion for explaining LTC insurance demand (see Eling and Ghavibazoo, 2019 for an overview), the role of ambiguity aversion has so far not been investigated. Evidence from other insurance contexts, however, suggests that ambiguity aversion is a core determinant of insurance demand decisions (e.g. Belissa, Lensink, and Van Asseldonk, 2020; Biener, Landmann, and Santana, 2019; Bryan, 2019).

Not only are LTC expenses uncertain, they also usually arrive several years after consumers consider buying LTC insurance. In the U.S. for instance, more than 80% of applicants for LTC insurance are younger than 65 (American Association for LTC Insurance, 2014). By contrast, the average age of nursing home residents at admission is around 80 (e.g. Kelly et al., 2010; Young et al., 2015). Considering the large time delay between purchasing and using LTC insurance, it is surprising that there is only scarce evidence on the role of time preferences for LTC insurance demand. To the best of my knowledge, only two studies address the relevance of time preferences for LTC insurance demand. A first study, by Kifmann, Roeder, and Schnekenburger (2010), provides a theoretical investigation of the role of non-standard time preferences (present biasedness) for LTC insurance demand, while the second study, by Huffman, Maurer, and Mitchell (2016), employs survey data to measure the effect impatience has on elderly subjects'

economic decision making. The latter study finds that impatience negatively affects the value of an end-of-life index. However, demand for LTC insurance is only one of the four equally weighted components of this index.¹ Hence, while the study provides evidence that impatience affects a general end-of-life index, it does not investigate the role of time preferences in LTC insurance demand in isolation. Additionally, as also mentioned by Huffman, Maurer, and Mitchell (2016), the size of the sample is rather small ($n < 500$) because several subjects did not respond to the questions comprising the end-of-life index. Therefore Huffman, Maurer, and Mitchell (2016) only provide partial evidence for the role of time preferences in LTC insurance demand.

In this study I provide empirical evidence on the role of attitudes toward uncertainty and standard time preferences (impatience) in explaining LTC insurance demand. I investigate their roles on the full study population, and on the subgroup of subjects with strong risk exposure. Subjects with strong risk exposure are more likely than the general study population to suffer from monetary losses due to LTC expenses. I investigate three components of risk exposure: bequest motives, beliefs about care need and family ties. I also focus on the subgroup of subjects expecting the insurance to perform (paying out an indemnity payment in case of a valid claim). Recent evidence suggests that beliefs about contract performance are important in the LTC context (Brown, Goda, and McGarry, 2012) and also other insurance contexts (e.g. Biener, Landmann, and Santana, 2019).

I link three surveys that were conducted in 2011 and 2012 on the American Life Panel, a panel that is representative of the U.S. population. The first of these surveys, conducted by Brown, Goda, and McGarry (2012), allows me to observe demand for LTC insurance, risk exposure, and beliefs about the performance of the insurance. Experimental decision tasks of the second and third surveys, conducted by Dimmock et al. (2016) and Yoong et al. (2019), allow me to elicit risk aversion, ambiguity aversion and impatience.²

My study follows a detailed pre-analysis plan, which was registered and time-stamped

¹The index assigns one point to each of the answers on the following four items: whether a subjects has long-term care insurance, whether she has assigned a power of attorney, whether she has a living will, and whether she had discussed end of life medical care plans with others.

²The three surveys that I link were initially designed to investigate the following topics: Dimmock et al. (2016) investigate whether ambiguity aversion helps to explain portfolio choice puzzles; Brown, Goda, and McGarry (2012) investigate, among others, the role of risk exposures and beliefs about performance for LTC insurance demand; and Yoong et al. (2019) investigate disparities in minority savings behavior (and use the time preference measure as a control variable).

at the Open Science Foundation (<https://osf.io/qpf4d/>).³ Following the main recommendations for the content of a pre-analysis plan laid out by Olken (2015), I pre-registered my hypotheses, data, variables, econometric specification, and statistical inference.⁴ Studies working with observational data are rarely pre-registered (Burlig, 2018). One exception in the finance literature is the study by Brown et al. (2020). This study was pre-registration prior to receiving access to proprietary, observational data. In contrast, this study employs non-proprietary survey data. I am unaware of any study in the household finance literature working with such a dataset that has registered a pre-analysis plan before accessing the data.

I find that, while attitudes toward uncertainty are unrelated to LTC insurance demand, time preferences (impatience) matter. In all of my regression specifications, the risk and ambiguity aversion coefficients are close to 0 and statistically insignificant. In contrast, impatient subjects are 9 percentage points less likely to demand LTC insurance than their patient counterparts. The effect of impatience is most pronounced among subjects with strong risk exposure and subjects who expect the insurance to perform. Among these subgroups impatient subjects are 15 - 17 percentage points less likely to demand insurance than their patient counterparts. Considering that the mean demand rate is 22% in the full sample and 25 - 27% in the subsamples, these effects are economically meaningful.

Attitudes toward uncertainty are unrelated to insurance demand even among subjects with strong risk exposure and subjects who expect the insurance to perform. Notwithstanding, and already documented in Brown, Goda, and McGarry (2012), differences in risk exposure and beliefs about contract-performance have a sizable (and statistically significant) effect on insurance demand. Both, risk exposure and optimistic beliefs about the performance of the insurance increase demand by roughly 10 percentage points. This suggests that, while changes in exposure to uncertainty matter, the extent to which they affect LTC insurance demand does not vary with consumers' attitudes toward uncertainty.

The puzzling co-existence of these findings may result from several potential explanations such as measurement issues relating to risk and ambiguity aversion, consumer's lack

³As proof that data was accessed after the upload of the pre-analysis plan, I added my data access request with a signing date to the OSF project (<https://osf.io/hq7gj/>).

⁴The focus of my pre-analysis plan was on the role of attitudes toward uncertainty. I therefore pre-registered hypotheses related to the effect of risk and ambiguity aversion. In addition, I stated that I benchmark these effects against the effect of time preferences (impatience).

of awareness of the financial risk posed by LTC costs, context-dependency of decisions, consumers copying behavior from social peers or following suggestions from financial advisors, and consumers not framing the decision stochastically. However, each of these potential explanations seems implausible to some extent.⁵ It is thus, unlikely that one explanation by itself explains why exposure to uncertainty matters, whereas attitudes toward uncertainty do not affect demand. Hence, it is more likely that a combination of these explanations provides an answer for the co-existence of these two findings.

The study contributes to three main strands of literature. First, the project adds to the recent literature that links non-standard risk preferences (e.g. ambiguity aversion, probability weighting, loss aversion) to household financial decision making (e.g. Dimmock et al., 2016; Dimmock et al., 2021, Goda et al., 2019; Noussair, Trautmann, and Van de Kuilen, 2014). A majority of these studies focus on stock market participation and portfolio allocation (e.g. Dimmock et al., 2016; Dimmock et al., 2021). An exception is the study by Goda et al. (2019), which investigates how (non-standard) time preferences and the exponential growth bias affect retirement savings. Ambiguity preferences have been shown to be an important determinant of insurance demand decisions in both, theoretical studies and experimental settings (e.g. Alary, Gollier, and Treich, 2013; Gollier, 2014; Biener, Landmann, and Santana, 2019; Bryan, 2019). However, to the best of my knowledge, no study exists that links measures of ambiguity aversion from a representative sample to real world insurance demand decisions. Consumers face ambiguity when assessing the likelihood of large LTC costs that usually arrive many years after a potential insurance purchase (e.g. Coe, Skira, and Van Houtven, 2015; Kemper, Komisar, and Alecxih, 2005; Lockwood, 2018; Zhou-Richter, Browne, and Gründl, 2010). Analyzing

⁵It seems implausible that measurement errors are the main drivers of the results because I can replicate the non-results on subsamples that are less likely to be subject to measurement errors (subjects giving consistent answers and subjects spending a sufficiently large amount of time on the questions). In addition, the effects remain close to 0 and statistically insignificant when I employ a qualitative measure of risk aversion (willingness to take financial risk) for a robustness check. Risk-exposure affects demands. Hence, the potential explanation that results are due to lack of risk awareness also seems implausible. Similar to risk and ambiguity aversion, impatience is elicited in a purely financial context. The effect of impatience is, however, statistically significant and economically meaningful. Hence, it is at least questionable that context-dependency can explain the non-results for risk and ambiguity aversion. If social ties or financial advisors drive financial decisions, it seems implausible that risk and ambiguity aversion correlate with other (complex) financial decisions (e.g. portfolio diversification). Related to the last potential explanation (consumers not framing the decision stochastically), note that the risk and ambiguity aversion measures also do not affect other insurance decisions (life, health, disability). Following the same explanation this would imply that consumers also view these set ups as non stochastically, which seems at least questionable.

the role of ambiguity aversion is therefore particularly interesting in the LTC insurance context. My results suggest that ambiguity aversion does not affect the demand for LTC insurance, even for consumers with strong risk exposure and consumers who expect the insurance to perform.

Second, the project contributes to the literature on the effect of time preferences on life-cycle financial decisions (e.g. Epper et al., 2020; Goda et al., 2019). These studies show that impatient (and also present-biased) consumers are less likely to save up a large wealth buffer (before entering retirement). I contribute to the literature by documenting that the same consumer types are also less likely to demand an insurance that can buffer large wealth losses in old age. Hence, impatient consumers, who already have a smaller-than-average wealth buffer, are also more likely to lose a sizable share (or even all) of their wealth when facing an LTC expenditure shock.

Third, my investigation contributes to the literature on demand-side factors limiting LTC insurance purchases. Brown and Finkelstein (2009) and Eling and Ghavibazoo (2019) provide reviews of this literature that identify a large set of factors that limit LTC insurance demand. Standard expected utility theory (EUT) models predict that the demand for LTC insurance increases with risk aversion (e.g. Mossin, 1968). However, the empirical findings on the effect of risk aversion are mixed (see Eling, Ghavibazoo, and Hanewald, 2021 for an overview). In this study I investigate whether two mediating factors - risk exposure and beliefs about the performance of the insurance - explain that insurance demand does increase with risk and ambiguity aversion. However, contrary to my pre-registered hypotheses, my results suggest that these factors do not affect the association between risk and ambiguity aversion and insurance demand.

The remainder of this paper is organized as follows. Section 2 provides information on the institutional background. Section 3 presents my hypotheses. Section 4 introduces the data and the empirical tests of my hypotheses. Sections 5, 6 and 7 present and discuss my results. Section 7 concludes.

2.2 Institutional Background

This study uses data from U.S. households. I therefore briefly review the institutional setting of LTC and LTC insurance in the U.S. here.

2.2.1 Utilization and Financing of LTC

Between 30 and 50 percent of older U.S consumers spend time in a nursing home at some point in their lives. The associated costs are large: one year in a private room ranges from \$55,000 to \$250,000 (Ameriks et al., 2020). The average duration of a stay in a nursing home is around 1.5 years for men and 2.5 years for women (e.g. Brown and Finkelstein, 2008; Brown and Finkelstein, 2009). These average numbers hide considerable heterogeneity, as the distribution of nursing home utilization is highly skewed to the right (that is, toward a longer stay). According to Ameriks et al. (2016), there is about a 1 in 6 chance of needing at least 3 years of LTC. As displayed in Table 2.1, a significant share of this risk remains uninsured. About 60 percent of LTC expenses are paid for by the public sector (Medicaid and Medicare), about 32 percent are paid by the individual either through insurance or directly, and a small share is paid by third parties and programs (e.g. charity). It is crucial to note that out-of-pocket payments account for a majority of the private expenditure share. These are nearly twice as large as payments by private LTC insurance.⁶ The small share of expenditures paid for by private insurance is driven by the fact that only 10 - 15% of the elderly in the U.S. have LTC insurance (e.g. Brown and Finkelstein, 2009; Nordman et al., 2016; Gottlieb and Mitchell, 2020). As displayed in Table 2.2 the share of LTC insurance holders increases with wealth, but even in the top wealth quintile it is less than 30%.

The two public sources of funding for long-term care are Medicare and Medicaid. Medicare is a nearly universal public health insurance for the elderly. The overwhelming majority (98%) of U.S. consumers, who are at least 65 years old, fulfill its eligibility requirements (Centers for Medicare and Medicaid Services, 2019). However, with respect to LTC, Medicare only covers expenses that are for recovery from acute illness (Centers for Medicare and Medicaid Services, 2021). LTC costs are only covered if they occur within 30 days of a hospital stay that lasted for at least three days. In addition, the coverage period is limited to 100 days (with a substantial co-pay after 20 days). After Medicare benefits are exhausted, additional long-term care services must be paid for out of pocket, by private insurance, or by the Medicaid program.

⁶The mean annual out-of-pocket spending in 2016 on LTC among subjects that need LTC but whose costs were not covered by Medicaid is \$41,782 (Cubanski et al., 2019). This estimate of spending is lower than median annual costs of a private room in a nursing home (\$92,000 in 2016) because several stays are shorter than 1 year. Throughout their entire life, consumers spent on average around \$72,000 from their own savings ("out of pocket") for LTC (Favreault and Dey, 2021).

	Public		Private		Other Third Party
Source	Medicare	Medicaid	Insurance	Out-of-pocket	All
Share	29%	31%	12%	20%	7%

Note: The table summarizes the financing of LTC in the U.S. in 2019. Data are from Centers for Medicare and Medicaid Services (2021).

Table 2.1: Financing of Long-term Care in the U.S.; 2019

Medicaid is a means-tested safety net for the indigent with no universal element to social protection (e.g. Muir, 2017; Weiner et al., 2020). Medicaid is a secondary payer relative to consumers’ own resources, meaning that its coverage only applies after an absolute majority of a consumer’s own resources are exhausted. Until that point, consumers bear the total financial burden of LTC themselves. Medicaid’s marginal contribution to LTC costs is therefore either 0 or 100 percent (Brown and Finkelstein, 2008). In order to receive financial support from Medicaid, an applicant’s monthly income and countable assets need to fall below specific thresholds. In most states the monthly income threshold for a single individual is set to 300% of the federal benefit rate (which is equal to the monthly maximum federal supplementary security income payment). In 2021, this is \$2,382 ($=\$794 \cdot 3$) per month (American Council on Aging , 2021). The (countable) asset threshold for a single individual is set at \$2,000 in 2021 for most states (American Council on Aging , 2021).⁷

It is important to note that even if consumers are eligible for Medicaid, they are expected to contribute all of their income with the exception of a personal need allowance that can be as little as 1% of the median income (Muir, 2017). Each state can set its own amount for the personal need allowance. In 2021 the median personal need allowance

⁷According to the American Council on Aging (2021), countable assets include cash, stocks, bonds, investments, promissory notes, credit union, savings and checking accounts, and real estate in which one does not reside. Additionally, an applicant’s home is added to the countable assets if the home equity (the fair market value of one’s home minus any debt on the home, such as a mortgage) does not exceed \$603,000. In order to ensure that hiding assets is difficult, the Medicaid program imposes a 3- to 5-year look-back period on assets. Income and asset limits are not as straightforward for married applicants as they are for single applications (American Council on Aging , 2021). For the income threshold note that the income of a non-applicant spouse is not used in determining income eligibility of their applicant spouse. In addition, the applicant can allocate some their income to their partner so that the partner can continue living at home. If both spouses are applicants, each spouse is eligible if his or her income falls below the state thresholds or if the combined income falls below twice the amount of the state threshold. For the asset threshold all of a married couples’ assets are considered jointly owned and are counted toward the asset threshold. If both spouses are applicants, the asset threshold is set to twice the threshold for a single individual. If only one spouse is an applicant, the other spouse can have countable assets valued at as high as \$130,380.

of all U.S. states is \$51, which is only marginally larger than the lower limit of \$30 per month that is forced by the federal government (American Council on Aging , 2021). An overview of the above-mentioned thresholds and allowance levels for the years 2021 and 2010 are displayed in Table 3.15 in the Appendix. In general, there is only little variation in these values over time or between states.

According to Kaiser Family Foundation (2017), 62% of all residents in nursing homes receive financial support from the Medicaid program. This shows that a majority of consumers that need LTC spend down nearly all of their assets for associated costs.⁸

Full Sample	By Wealth Quintile				
	Top	Fourth	Third	Second	Bottom
13.8%	26.9%	19%	10.7%	6.6%	4.1%

Note: The table shows LTC insurance take-up rates by wealth quintile. Data are from Brown and Finkelstein (2007).

Table 2.2: Long-term Care Insurance Take-up Rates U.S. 2008

2.2.2 The Private Market for LTC Insurance

The market for LTC insurance is highly concentrated. The three largest companies account for nearly half the market, as measured by premiums and number of policies (American Association for LTC Insurance, 2019). The vast majority (about 85%) of LTC insurance policies are sold through the individual, non-group market (American Association for LTC Insurance, 2019). LTC insurance policies specify the benefit scheme and qualification criteria. Policy holders usually qualify for benefits if they need either (i) assistance with at least two activities of daily living, or (ii) supervision because of cognitive impairment (Tumlinson, Aguiar, and Watts, 2009; Cornell et al., 2016). LTC insurance benefit schemes differ in four main dimensions: the daily benefit amount, the benefit period, the elimination period, and inflation protection. The daily benefit amount is the maximum the insurance will pay for services received on a given day. It usually ranges from \$100 to \$300, and the mean over the last years was around \$150 (Nordman et al., 2016). The benefit period specifies the maximum length of cost coverage. It usually ranges from 3 to 5 years with a mean of around 4 years (American Association for LTC

⁸The LTC system in the U.S. which offers no universal element of protection and, thus, forces consumers to spend down a majority of assets before receiving any public support, is unique among OECD countries (e.g. Muir, 2017; Weiner et al., 2020).

Insurance, 2014; Nordman et al., 2016). The elimination period (often also referred to as the deductible period) specifies the number of days that an individual must be receiving care before the insurance company begins to pay. It ranges from 0 to 100 days, and its mean over is around 90 days (American Association for LTC Insurance, 2014; Tumlinson, Aguiar, and Watts, 2009; Nordman et al., 2016). Close to 75% of all policies contain an inflation protection. Their annual increase in benefits is between 2 and 5% (Nordman et al., 2016).

A majority of consumers (>80%) are younger than 65 years old when applying for LTC insurance (American Association for LTC Insurance, 2014; Tumlinson, Aguiar, and Watts, 2009; Nordman et al., 2016; Lifeplan, 2017). Medical underwriting of policies screens out between 15 and 30% of all applicants (American Association for LTC Insurance, 2014; Tumlinson, Aguiar, and Watts, 2009; Nordman et al., 2016). For accepted applicants the age and gender are core determinants of the insurance premium. Table 2.3 shows the average annual premium for a 55-year-old and 65-year-old male and female that purchase an LTC insurance policy in 2021 with a maximum benefit amount of \$165,000 (corresponding to a daily benefit of \$150 for a three-year benefit period). The premiums range between \$950 and \$2,700, are larger for females, and increase with age. Brown and Finkelstein (2007) estimate that the average LTC insurance policy has a load of 0.18, i.e. for every dollar that is invested in LTC insurance, the expected discounted return is 82 cents. This is comparable to the load on life annuities (0.15 to 0.25; see Mitchell et al., 1999) but higher than the load on health insurance policies (0.04 to 0.15; see Karaca-Mandic, Abraham, and Phelps, 2011). Although loads on LTC insurance policies are substantial, profits for insurers remain low (Nordman et al., 2016; Braun, Kopecky, and Koreshkova, 2019). The main reasons for this are (i) high promotion costs, (ii) high administrative expenses associated with underwriting and claim processing, and (iii) the intertemporally risky nature of LTC insurance policies, which forces insurers to hold reserves to provision against adverse future developments in claims (see Nordman et al., 2016 and Braun, Kopecky, and Koreshkova, 2019 for more details).

	55-year-old	65-year-old
Women	\$1500	\$2700
Men	\$950	\$1700

Note: The figure shows the average LTC insurance premium for an insurance with a maximum benefit amount of \$165,000. Data are from (American Association for LTC Insurance, 2021).

Table 2.3: Average annual LTC insurance Premiums in the U.S. 2021

2.3 Hypotheses

Consumers are, in general, aware of the LTC expenditure risk they face (e.g. De Nardi, French, and Jones, 2010; Ameriks et al., 2020). Consumers can choose between three options to finance LTC expenditures. First, they can rely on public sources (Medicare and Medicaid); second, they can buy LTC insurance; or, third, they can self-insure by saving significant amounts of money to pay for care costs out of their own pocket (buffer-stock savings in expectation of large LTC costs are, for instance, documented in Ameriks et al., 2020). I pre-registered hypotheses addressing the effect risk and ambiguity aversion have on consumer’s choice for LTC insurance and self-insurance. However, after accessing the data, my analysis suggests that the pre-registered measure for self-insurance does not capture an insurance motive, as the measure of self-insurance is neither affected by risk exposure nor by beliefs about the performance of a LTC insurance; see Appendix 3.8.1 for details. I therefore show only my hypotheses related to LTC insurance.

Under standard EUT, the willingness to pay for insurance increases with risk aversion (Mossin, 1968). Extensions of classical insurance demand models that add ambiguity about potential losses predict that the willingness to pay increases with both, risk and ambiguity aversion (e.g. Alary, Gollier, and Treich, 2013; Biener, Landmann, and Santana, 2019; Peter and Ying, 2020). Empirical evidence from other insurance contexts suggests that ambiguity aversion is at least as important for insurance demand decisions as risk-aversion (Belissa, Lensink, and Van Asseldonk, 2020; Biener, Landmann, and Santana, 2019; Bryan, 2019). In the context of LTC, ambiguity is particularly present. Potential payouts of an LTC insurance policy usually arrive several years after the purchase, and consumers face (considerable) ambiguity when assessing both, the likelihood of needing LTC and the length of time for which care will be required (e.g. Coe, Skira, and Van Houtven, 2015; Kemper, Komisar, and Alecxih, 2005; Zhou-Richter, Browne, and Gründl, 2010). Additionally, note that empirical evidence on the effect risk aversion

has on LTC insurance demand is mixed (see Eling, Ghavibazoo, and Hanewald, 2021 for an overview; while some studies find (mild) positive effects, others find insignificant or even negative effects). I therefore expect that ambiguity aversion is a more important determinant of LTC insurance demand than risk aversion.

Following the explanation above, I pre-registered a first hypothesis on the average effect of risk and ambiguity aversion.⁹

H1a: Risk Aversion, Ambiguity Aversion and LTC Insurance Demand: Risk aversion and ambiguity aversion positively affect LTC insurance demand. The effect is stronger for ambiguity aversion.

In pre-registered tests of heterogeneous effects, I examine whether the investigated effects are related to two mediating factors. These are beliefs about risk exposure and beliefs about contract performance. I test the following first auxiliary hypothesis:

H1b: The Role of Risk Exposure I: For consumers with large risk exposure, risk aversion and ambiguity aversion affect LTC insurance demand more strongly than for consumers with weaker risk exposure.¹⁰

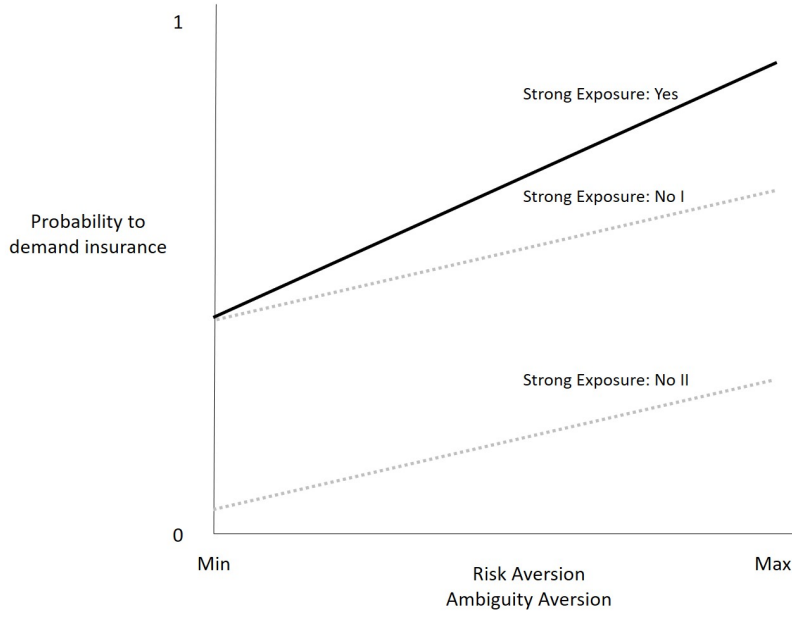
Figure 3 provides a graphical representation of hypothesis H1b. The solid black line ("Strong Exposure: Yes") displays the positive effect of risk and ambiguity aversion on the probability of buying insurance that I expect for consumers with strong risk exposure. The two dotted gray lines ("Strong Exposure: No I" and "Strong Exposure: No II") show examples of weaker effects that translate into less steep lines. Note that an additional shift in the intercept (as the case for the "Strong Exposure: No II" line) is possible without affecting the hypothesis.¹¹

Potential contract non-performance adds a second layer of risk and uncertainty to insurance settings. An indemnity may not be paid out although a loss occurs. The negative effect of non-performance on insurance demand is expected to be most pronounced among risk- and ambiguity-averse individuals (Biener, Landmann, and Santana, 2019). Non-performance therefore reduces the positive effect of both risk aversion and ambiguity aversion on insurance demand compared to what should be observed otherwise. I

⁹Following classical economic theory, I assume that consumers' attitudes toward uncertainty reflect fundamental economic preferences. These preferences, thus, causally affect decision making.

¹⁰As pre-specified in my pre-analysis plan, I investigate three components of risk exposure: bequest motives, beliefs about care need and family ties.

¹¹If there is only a shift in the intercept without decreased steepness of the line then the hypothesis does not hold. In this case, strong risk exposure leads to a uniform reduction in insurance demand probability, irrespective of the individuals' risk and ambiguity preferences.



Note: The figure shows potential effects that risk or ambiguity aversion (on the x-axis) can have on the probability to buy insurance (on the y-axis) for subjects with strong risk exposure (Strong Exposure: Yes) and subjects with weaker risk exposure (the two other lines).

Figure 2.2: Illustration of Potential Effects

therefore test the following second auxiliary hypothesis for risk and ambiguity aversion:

H1c: The Role of Contract Performance I: For consumers who believe that the insurance will perform, risk aversion and ambiguity aversion affect insurance demand more strongly than for consumers who believe that the insurance may not perform

Potential payouts of an LTC insurance policy usually arrive several years after the purchase and consumers differ in how strongly they discount future outcomes (e.g. Epper et al., 2020). I therefore expect that impatience is negatively related to insurance demand. Additionally, I expect that the effect of impatience is most pronounced among consumers who are likely to depend on indemnity payments in the future (i.e. consumers with strong risk exposure) and consumers who believe that valid indemnity payments will be paid (i.e. consumers who expect the insurance to perform).¹² I therefore test the following three exploratory hypotheses.¹³

H2a: Impatience and Insurance Demand: Impatience negatively effects insurance

¹²For their counterparts, i.e. consumers with weak risk exposure and consumers who believe that an insurance may deny reasonable claims, future payouts are less likely and, hence, impatience has a weaker effect when evaluating the insurance.

¹³I have pre-registered an investigation of the role of time preferences as an additional analysis with the goal of benchmarking potential effects of risk and ambiguity preferences against an effect of time preferences (see page 19 of the pre-analysis plan). I, however, have not pre-registered explicit hypotheses related to time preferences. I therefore refer to these three hypotheses as exploratory.

demand.

H2b: The Role of Risk Exposure II: For consumers with strong risk-exposure, impatience affects insurance demand more strongly for consumers with weaker risk exposure.

H2c: The Role of Contract Performance II: For consumers who believe that the insurance will perform, impatience affects insurance demand more strongly than for consumers who believe that the insurance may not perform.

2.4 Data and Methodology

2.4.1 Sample

I link three surveys that were conducted on a representative sample of the U.S. population (RAND American Life Panel) in 2011 and 2012. American Life Panel (ALP) subjects are regularly invited to participate in (online) surveys. In 2011 and 2012 the ALP included a total of approximately 4,500 subjects (RAND, 2017). The ALP assigns each subject a unique identifier which enables me to link the surveys.

Table 2.4 summarizes the core components of the surveys that I link together for this study. The first survey was conducted by Brown, Goda, and McGarry (2012) in 2011. A total of 1,569 subjects from the age group ≥ 50 participated. I use this survey to obtain measures of LTC insurance demand, beliefs about risk exposure, and beliefs about contract performance. The second was conducted by Dimmock et al. (2016) in 2012. The third survey was conducted by Yoong et al. (2019) in 2011. Roughly 3,000 subjects from the age group 18-70 participated in each of these surveys. I use questions from these two surveys to elicit measures of risk aversion, ambiguity aversion, and impatience. My study sample consists of the $n = 1,109$ subjects that participated in all three surveys.

I compare my study sample to the participant pool of the individual surveys. These comparisons show no unexpected differences, implying that linking the three surveys kept their representative nature. By design I observe statistically significant differences in the age structure, as Brown, Goda, and McGarry (2012) only invited subjects from the age group ≥ 50 (details can be found in Table 3.68 in the Online Appendix).

My study sample deviates from the pre-registered sample in two ways. First, I am investigating the effects of risk and ambiguity aversion on the overlap of all three surveys and not (as pre-registered) only on the overlap of the Dimmock et al. (2016) and Brown,

Survey	Time	Age Group	Core Variables
Brown, Goda, and McGarry (2012)	05.2011 - 09.2011	≥ 50 years n = 1,569	Demand for LTCI, Family Ties, Bequests Motives, Care Needs Contract Performance
Dimmock et al. (2016)	03.2012 - 04.2012	18 - 70 years n = 3,285	Risk Aversion, Ambiguity Aversion
Yoong et al. (2019)	06.2011 - 08.2011	18 - 70 years n = 3,059	Impatience

Note: The table summarizes the key elements of the three ALP surveys that are linked to construct the sample.

Table 2.4: Overview of Surveys

Goda, and McGarry (2012) surveys. The reason for this is that I did not know that linking the third survey only reduces the sample by 39 observations prior to receiving access to the data. Second, I do not exclude the subjects that spent less than 2 minutes on the ambiguity aversion decision tasks. Subjects make between 1 and 4 decisions in the ambiguity aversion decision tasks. Excluding subjects based on the total time neglects differences in the number of decisions that were made. As shown in Section 3.8.1 of the Online Appendix, results of this paper are not affected by these minor adjustments in the sample selection.

2.4.2 Dependent Variables: LTCI Demand

My main outcome variable is an indicator of subjects' demand for LTC insurance ("LTCI Demand"). This indicator variable is constructed using three survey questions concerning (i) whether a subject owns LTC insurance; (ii) in case she does not know the answer to the previous question, whether it is more likely that she owns LTC insurance than not; and, (iii) whether she applied for an LTC insurance policy, but the application was denied. If the answer to any of these three questions is "Yes", the indicator variable is set to 1; otherwise, it is set to 0. The exact wording and answer options to the three survey questions can be found in Appendix 3.8.1. In my sample, 16% report to own an LTC insurance policy, 4% report that it is more likely they own an LTC insurance than not, and 1.5% report that they had an application for LTC insurance rejected. Hence, as displayed in Table 2.5, the outcome variable is set to 1 for 21.5% of the subjects.

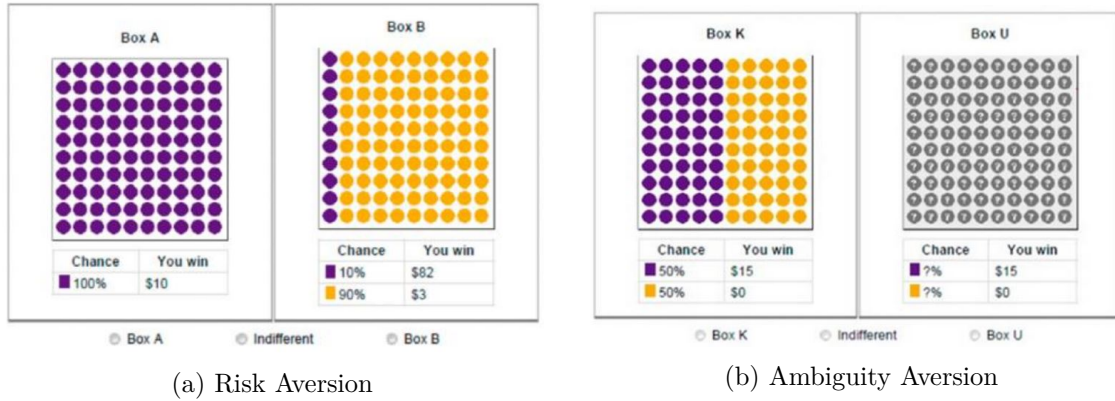
	Mean	Min	P(25)	P(50)	P(75)	Max	SD	N
<u>Outcome Variable</u>								
LTCI Demand (1 = Yes)	0.22	0.00	0.00	0.00	0.00	1.00	0.41	1,109
<u>Explanatory Variables</u>								
Risk Aversion	0.40	−0.50	0.14	0.48	0.70	0.96	0.40	1,109
Ambiguity Aversion	0.19	−0.44	−0.09	0.03	0.12	0.47	0.20	1,109
Impatience	2.73	1.00	2.00	3.00	3.00	4.00	1.05	1,109
<u>Mediating Variables</u>								
Insurance Performs (1 = Yes)	0.36	0.00	0.00	0.00	1.00	1.00	0.48	1,109
Bequest Motives (1 = Yes)	0.52	0.00	0.00	1.00	1.00	1.00	0.50	1,109
No Family Ties (1 = Yes)	0.73	0.00	0.00	1.00	1.00	1.00	0.45	1,109
Care Need (1 = Yes)	0.44	0.00	0.00	0.00	1.00	1.00	0.50	1,109
<u>Covariates</u>								
Number of Children	2.10	0.00	1.00	2.00	3.00	7.00	1.67	1,109
Financial Literacy	2.21	0.00	2.00	2.00	3.00	3.00	0.70	1,109
General Trust	2.19	1.00	2.00	2.00	3.00	4.00	0.70	1,109
Working (1 = Yes)	0.60	0.00	0.00	1.00	1.00	1.00	0.49	1,109
Family Income	3.19	1.00	2.00	3.00	5.00	5.00	1.42	1,109
College (1 = Yes)	0.58	0.00	0.00	1.00	1.00	1.00	0.49	1,109
Civil Status (1 = Relationship)	0.67	0.00	0.00	1.00	1.00	1.00	0.472	1,109
White (1 = Yes)	0.92	0.00	1.00	1.00	1.00	1.00	0.28	1,109
Male (1 = Yes)	0.42	0.00	0.00	0.00	1.00	1.00	0.49	1,109
Age	2.34	1.00	1.00	2.00	3.00	4.00	1.06	1,109

Note: The table presents summary statistics for my outcome, mediating, explanatory, and control variables. Panel A displays detailed summary statistics for all variables. Variable definitions are presented in Section 3.8 of the Online Appendix.

Table 2.5: Summary Statistics

2.4.3 Explanatory Variables: Risk Aversion, Ambiguity Aversion, Impatience

My first two explanatory variables are indicators of risk and ambiguity aversion that are elicited in the Dimmock et al. (2016) survey. I only provide a short summary of the elicitation procedure here and refer to Dimmock et al. (2016) for a detailed discussion. For the risk aversion measure ("Risk Aversion") subjects make a sequence of choices between a risky and a certain option. An example decision task can be found in Figure 2.3 (a). The risk distribution of the risky option in a specific choice task depends on subjects choices in the prior tasks. If a subject chooses the risky option in the prior task, then the risky option is adjusted such that it becomes less attractive in the next choice task. The goal of this staircase method is to elicit the indifference point between a risky and a certain option. This point is then used to estimate the risk aversion parameter using a power utility, where the power coefficient is limited to the range from 0 to 1.5. Risk aversion is defined as 1 minus the power function coefficient, and varies from -0.5 (strongest level of risk seeking) to +1 (strongest level of risk aversion). A coefficient larger than 0 implies risk aversion. As displayed in Table 2.6 and Table 2.5, a majority of subjects (82 %) are classified as risk averse and the mean risk aversion parameter is 0.39.



Note: The figures are taken from Dimmock et al. (2016) and present examples of the survey questions to elicit risk and ambiguity aversion.

Figure 2.3: Decision Tasks to Elicit Risk and Ambiguity Aversion

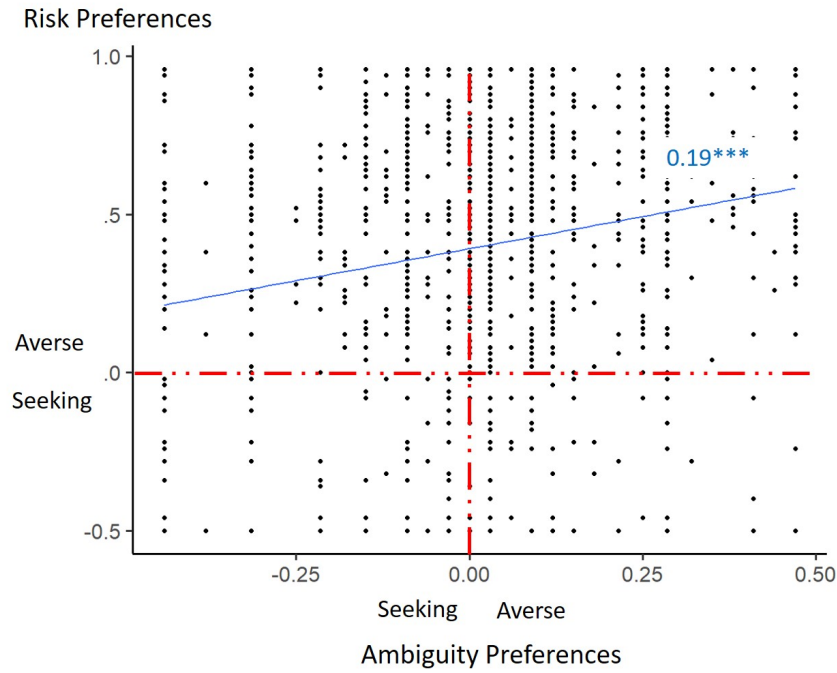
Dimmock et al. (2016) elicit ambiguity aversion through (repeated) choices between two options: one risky and the other ambiguous. Figure 2.3 (b) displays an explanatory decision tasks. The payout of the risky option in a specific choice task depends on subjects choices in the prior tasks. If a subject chooses the ambiguous option in the prior task,

then the risky option is adjusted such that it becomes more attractive in the next choice task. The goal of the staircase method is to elicit the indifference point for the ambiguous option (i.e. the share of purple balls that is required in the risky option so that a subject is indifferent between the risky and the ambiguous option). The ambiguity aversion measure ("Ambiguity Aversion") is then calculated as $0.5 - q$, where q refers to the share of purple balls in the risky option that implies indifference. Ambiguity Aversion varies from -0.5 (strongest level of ambiguity seeking) to 0.50 (strongest level of ambiguity aversion). A coefficient larger than 0 implies ambiguity aversion. Roughly half of the subjects (52 %) are classified as ambiguity averse (see Table 2.6) and the mean ambiguity aversion parameter in my sample is 0.19 (see Table 2.5). Figure 2.4 displays the distribution of the risk and ambiguity parameters in my sample. While there is a (weak) positive correlation (19%), the dataset contains sufficient variation in these two preferences.¹⁴

My third main explanatory variable ("Impatience") is an indicator of time preferences that is elicited in the survey of Yoong et al. (2019). In their staircase procedure, subjects make two choices between receiving \$1000 + \$A in a year or \$1000 today. The amount A is set to \$250 in the first task. Depending on the choice in this task, A is set either set to \$650 or \$100 for the second task. Subjects' answers to these questions allow me to set the impatience variable to 1 (least impatience), 2, 3, or 4 (most impatience). The impatience variable is, for instance, set to 1 for subjects who prefer receiving \$1100 (the smallest possible amount) in a year to \$1000 today, and it is set to 4 for subjects who prefer receiving \$1000 today to \$1650 (the largest possible amount) in a year. Panel B of Table 2.6 shows the distribution of the impatience variable.¹⁵

¹⁴The distribution of risk and ambiguity aversion in my sample is similar to the distribution of these preferences in the (larger) Dimmock et al. (2016) sample (see Figure 3.16 in the Appendix for a comparison). A weak positive correlation between risk and ambiguity aversion is also documented by other studies (e.g. Dean and Ortoleva, 2019). However, it is not a general pattern, as other studies (with different subject groups and different elicitation methods) also find weak negative correlations (e.g. Dimmock, Kouwenberg, and Wakker, 2017), or no (statistically significant) correlation (e.g. Cohen, Tallon, and Vergnaud, 2011; Kocher, Lahno, and Trautmann, 2018).

¹⁵In my sample the correlations between risk aversion and impatience, and ambiguity aversion and impatience are close to 0 and statistically insignificant (-0.018 for risk aversion; -0.068 for ambiguity aversion). The studies by Abdellaoui et al. (2013) and Cohen, Tallon, and Vergnaud (2011) that employ alternative elicitation procedures also estimate correlations that are close to 0 and statistically insignificant.



Note: The figure shows the joint distribution of the ambiguity aversion parameter (on the x-axis) and the risk aversion parameter (on the y-axis) in my study sample. The blue line displays the correlation of these two parameters, which is 0.19 and highly statistically significant (***) denotes significance at the 1%-level). The two red lines split the sample into ambiguity (risk) seeking and ambiguity (risk) averse.

Figure 2.4: Distribution of Risk and Ambiguity Preferences

Panel A: Risk and Ambiguity Preferences

	Yes	No
Risk Aversion	82%	18%
Ambiguity Aversion	52%	48%

Panel B: Time Preferences

	1 (Min)	2	3	4 (Max)
Impatience	17%	20%	33%	28%

Note: Panel A shows the share of subjects that are classified as risk averse or ambiguity averse. As in Dimmock et al. (2016), subjects are classified as risk averse if the coefficient of the calibrated power utility function is smaller than 1, and ambiguity averse if they prefer the risky option with a success probability of 50% over the option with an ambiguous success probability (see the corresponding decision task displayed in Figure 2.3). Panel B summarizes the classification of subjects in impatience types.

Table 2.6: Summary: Explanatory Variables

2.4.4 Mediating Variables

My auxiliary hypotheses address the role of risk exposure and contract performance. As pre-registered, I employ three risk exposure measures. These are family ties, bequest motives and beliefs about care need. To split the sample I construct indicator variables using survey questions of Brown, Goda, and McGarry (2012). Note that for each of the questions listed below the answer options are "Strongly Agree", "Agree", "Neither Agree nor Disagree", "Disagree", and "Strongly Disagree". The exact wording of the survey questions and distribution of responses is displayed in Appendix 3.8.1.

- Bequest Motives (Risk Exposure I): the indicator is set to 1 for subjects who answer "Strongly Agree" or "Agree" to a question on whether it is important to leave an inheritance.
- No Family Ties (Risk Exposure II): the indicator is set to 1 for subjects who do not answer "Strongly Agree" or "Agree" to a question on whether family members will be able to take care of them if needed.
- Care Need (Risk Exposure III): the indicator is set to 1 for subjects who answer "Strongly Agree" or "Agree" to a question on whether at some point in the future it is likely that they will no longer be able to live independently due to health reasons.
- Insurance Performs: There are two questions on whether the insurance may not perform, (i) due to a denial of reasonable claims, or (ii) due to third party risk (i.e. bankruptcy of the insurance company before the claim can be made). The indicator is set to 1 for subjects who do not answer "Strongly Agree" or "Agree" to any of the two questions.

As displayed in Table 2.7, the number of observations is sufficiently large in all considered subsamples. The mediating variables are related to insurance demand as expected. Demand is larger among subjects with stronger risk exposure (Bequest Motives: Yes; No Family Ties: Yes; Care Need: Yes) and among the subjects who expect the insurance to perform (Insurance Performs: Yes).

	Sample Size	LTCI Demand (Mean)
Bequest Motives: Yes	572	0.26
Bequest Motives: No	537	0.17
No Family Ties: Yes	805	0.22
No Family Ties: No	304	0.19
Care Need: Yes	482	0.27
Care Need: No	627	0.17
Insurance Performs: Yes	401	0.27
Insurance Performs: No	708	0.18

Note: The table summarizes the total number of observations and the mean of the outcome variable LTCI demand for each of the eight subgroups considered in this study.

Table 2.7: LTC Insurance Demand by Group

2.4.5 Covariates

I employ the ALP Baseline survey to obtain information on the following variables: the number of children, working status, family income (in \$25,000 baskets from 1: $\leq$ \$25,000 to 5: $>$ \$125,000), college education, civil status, whether a subject self-identifies as "white", gender, and age (in 5 year baskets from 1: $<$ 55 years to 4: $>$ 65 years. Additionally, survey questions posed by Dimmock et al. (2016) and Brown, Goda, and McGarry (2012) allow me to elicit a measure of financial literacy (number of correct answers to three financial questions) and a general measure of trust (ranging from 1, "Most people can be trusted.", to 4, "You cannot be too careful."). Summary statistics of these variables are displayed in Table 2.5.

Importantly, note that I do not control for subjects' actual net wealth, as I expect net wealth to be causally related to my explanatory variables (i.e. subjects decide to self-insure as a response to the risk or uncertainty they face; see Ameriks et al., 2020). Controlling for endogenous variables may yield biased estimates because these already explain parts of the true effect (see Lechner (2008), for a discussion). I, however, control for the level of education. Education is a proxy for lifetime income (e.g. Tamborini, Kim, and Sakamoto, 2015; Goldrick-Rab et al., 2016), as well as for the likelihood of a sizable inheritance (e.g. Charles and Hurst, 2003; Machin and Vignoles, 2004, Lovenheim and Reynolds, 2013). Considering that I control for financial literacy, the level of education mainly captures major components of net wealth.

2.4.6 Methodology

Main Analysis: In order to test my main hypothesis H1a, I standardize the risk and ambiguity aversion measure (subtract the mean and divide by the standard deviation). I then estimate the following regression specification on the full sample:

$$\begin{aligned} \text{LTCI Demand}_i = & \beta_0 + \beta_1 \cdot \text{Risk Aversion}_i + \beta_2 \cdot \text{Ambiguity Aversion}_i + \beta_3 \cdot \text{Impatience}_i \\ & + \beta_4 \cdot \text{Risk Exposure}_i + \beta_5 \cdot \text{Insurance Performs}_i + \beta_x \cdot X_i. \end{aligned} \quad (2.1)$$

The outcome variable captures the demand of subject i for LTC insurance. The main explanatory variables are (standardized) risk aversion, (standardized) ambiguity aversion, and impatience.¹⁶ The regression specification further includes the mediating variables (risk exposure and beliefs about the performance of the insurance) and subject-specific covariates (X_i). Table 2.5 lists all variables and their summary statistics.

According to my hypothesis H1a, I expect that $0 < \beta_1 < \beta_2$. I first use standard 5% significance levels to judge whether the two coefficients are significantly different from 0. I then test whether potential differences between the two coefficients are statistically significant. For this I conduct a post-estimation z-Test. I test the null hypotheses $H_0 : \beta_1 \geq \beta_2$ against the one-sided alternative hypotheses $H_a : \beta_1 < \beta_2$.¹⁷ According to my hypothesis H2a I expect $\beta_3 < 0$. I again use standard 5% significance levels to judge whether the impatient coefficients are significantly different from 0.

To test my auxiliary hypothesis H1b and H2b (Role of Risk Exposure I), I split subjects into two groups. Subjects with (strong) risk exposure are assigned to Group 1, whereas the others are assigned to Group 2. Within the two groups, I then proceed as explained above and again estimate the same regression specification. According to my hypothesis, I expect that the coefficients β_1 , β_2 and β_3 are smaller in Group 2 (the group with smaller risk exposure) than in Group 1. To test whether potential differences in the coefficients are statistically significant, I conduct post-estimation (one-sided) z-

¹⁶The survey questions allow me to sort subjects into four impatience groups. The impatience variable in the regression specification is, thus, a factor variable. For the regressions I, thus, estimate three impatient dummies (Impatience: 2, Impatience: 3, Impatience: 4 (max)).

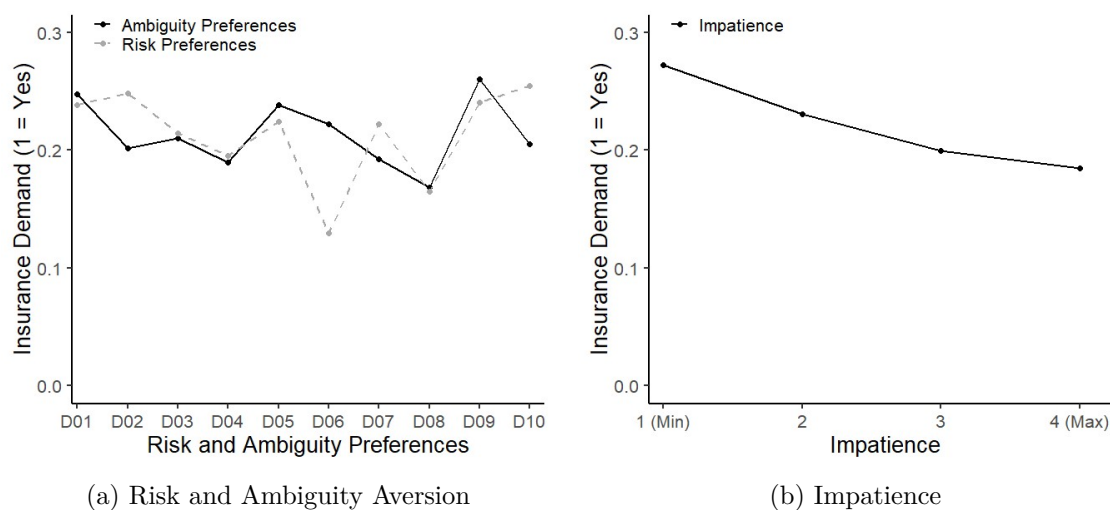
¹⁷The test statistic Z is calculated as $Z = \frac{\beta_1 - \beta_2}{\sqrt{SE(\beta_1) + SE(\beta_2)}}$. Here SE denotes the standard error of the coefficients. Under the null hypothesis H_0 , Z follows a standard normal distribution (Paternoster et al., 1998).

Tests. These tests allows all control variables to vary across the two subsamples. This is crucial, as my grouping variable is not an exogenous treatment assignment. For the test of my other auxiliary hypotheses H1c and H2c (Role of Contract Performance) I proceed identically except that I use different grouping variables.

2.5 Results

2.5.1 Average Effects

Figure 2.5 provides a visual inspection of the average effects that risk aversion, ambiguity aversion, and impatience have on the demand for LTC insurance. Panel (a) depicts insurance demand within risk and ambiguity aversion deciles. Note that subjects in the first decile (D1) are the least risk/ambiguity averse whereas subjects in the tenth decile (D10) are the most risk/ambiguity averse. Both lines vary without any systematic pattern around the sample mean (21.5 %). Hence, the visual inspection suggests that risk and ambiguity aversion have no effect on LTC insurance demand.



Note: The figures display the average LTC insurance demand rate by risk and ambiguity aversion deciles (Panel a) and four impatience levels (Panel b).

Figure 2.5: Average Effects

Panel (b) of Figure 2.5 depicts insurance demand within each of the four impatience groups. Note that subjects in the first group are the least impatient whereas subjects in the last group are the most impatient. The visual inspection suggests that LTC insurance demand decreases with impatience. Insurance demand decreases from 27.3% for the least

impatient to 18.4% for the most impatient.

Table 2.8 displays the regression results estimated on the full sample. Note that the table only presents the main coefficients of interest. The complete regression output is shown in Table 3.40 in the Appendix. In specifications (1), (2), and (3) I regress insurance demand only on one of the three explanatory variables (risk aversion, ambiguity aversion, impatience). Specification (4) is my main regression specification. It includes the three explanatory variables, the mediating variables, and all control variables.

	<i>Dependent variable: LTC Insurance Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.008 (0.012)			−0.012 (0.012)
Ambiguity Aversion		−0.005 (0.012)		−0.008 (0.013)
Impatience: 2			−0.042 (0.040)	−0.036 (0.040)
Impatience: 3			−0.073** (0.036)	−0.041 (0.037)
Impatience: 4 (Max)			−0.088** (0.037)	−0.036 (0.040)
Bequest Motives				0.076*** (0.025)
No Family Ties				0.012 (0.028)
Care Need				0.097*** (0.025)
Insurance Performs				0.100*** (0.026)
Constant	0.215*** (0.012)	0.215*** (0.012)	0.273*** (0.029)	0.180** (0.088)
Mean Dep. Var	0.22	0.22	0.22	0.22
Controls	No	No	No	Yes
Observations	1,109	1,109	1,109	1,109
R ²	0.0004	0.0001	0.006	0.071

Note: The table shows the results of an OLS regression. The dependent variables measure subject's demand for LTC insurance. Robust standard errors are reported in parentheses. *, **, *** denote significance at the 10-, 5-, and 1-percent level.

Table 2.8: Average Effects of Risk and Ambiguity Aversion (Multivariate)

In line with the visual inspection, the coefficients for risk and ambiguity aversion are close to 0 and statistically insignificant in all specifications. The impatience dummies are negative, increasing in magnitude and statistically significant in the univariate spec-

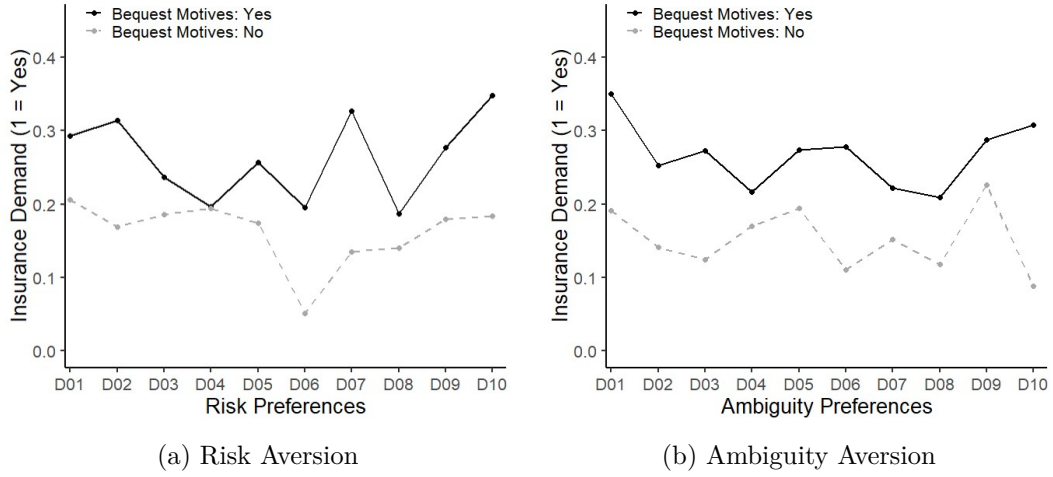
ification (3). In the multivariate specification (4) the impatience dummies are weaker in magnitudes and lose statistical significance. The mediating variables - risk exposure (measured by bequest motives, no family ties and care need) and beliefs about performance of the insurance - are related to insurance demand as expected. Subjects with stronger risk exposure and subjects who expect the insurance to perform are more likely to demand insurance than their counterparts. The coefficient of the risk exposure and insurance performance dummies are qualitatively and quantitatively similar to the results of Brown, Goda, and McGarry (2012). Two of the three risk exposure measures (bequest motives and care need) and also optimistic beliefs about the performance of the insurance increase insurance demand by between 7 and 10 percentage points, which is a sizable effect considering that the mean demand rate is only 21.5%. The effect of the third risk exposure measure (no family ties) is small (it only increases insurance demand by 1.2 percentage points) and statistically insignificant.

2.5.2 Heterogeneous Effects

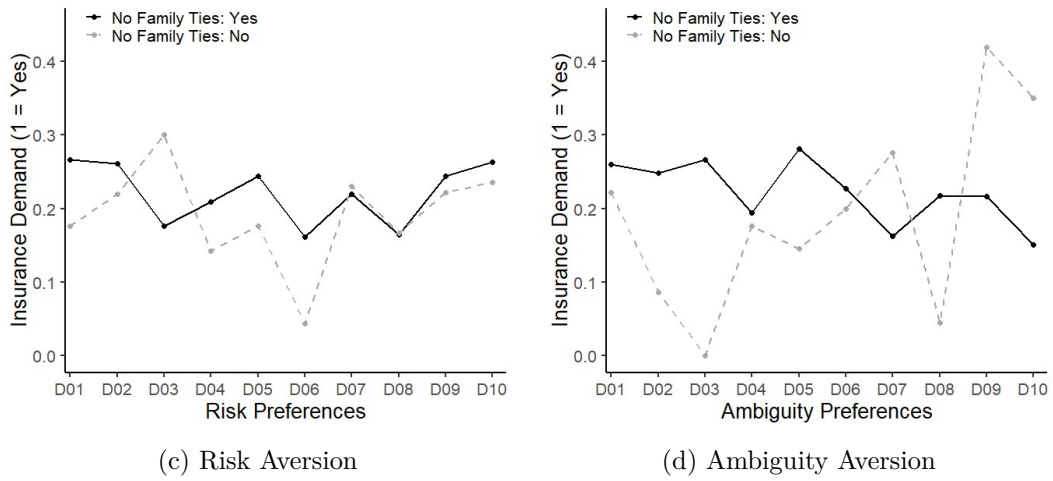
I expect stronger effects of risk aversion, ambiguity aversion, and impatience on insurance demand for subjects with (strong) risk exposure. As pre-registered, I employ three exposure measures: bequest motives, no family ties, and care need. A visual inspection of the results is displayed in Figures 2.6 and 2.7. The figures of Panel A show the results for the first risk exposure measure (bequest motives). The first two figures in 2.6 display insurance demand by risk or ambiguity aversion deciles, respectively, distinguishing between subjects with bequest motives (the filled black line) and without bequest motives (the dashed gray line). The figures suggest that there is not even a systematic relationship between risk and ambiguity aversion and insurance demand among subjects with (strong) risk exposure.

The first figure in 2.7 displays LTC insurance demand by impatience levels. In line with my hypotheses, the negative effect of impatience seems to be more pronounced among subjects with strong risk exposure (the filled black line). Demand decreases monotonically from 33% for the least impatient to 19% for the most impatient subjects. For subjects with weaker risk exposure (the dashed gray line), there seems to be no systematic relationship between impatience and insurance demand. Panel B and Panel C of Figure 2.6 and 2.7 display visual inspections for the two other risk exposure measures (no

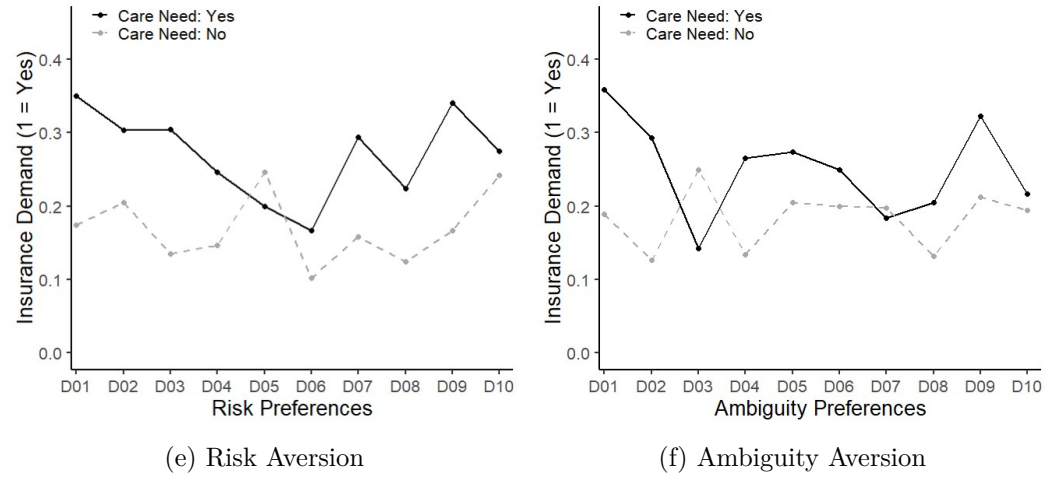
Panel A: Bequest Motives



Panel B: No Family Ties

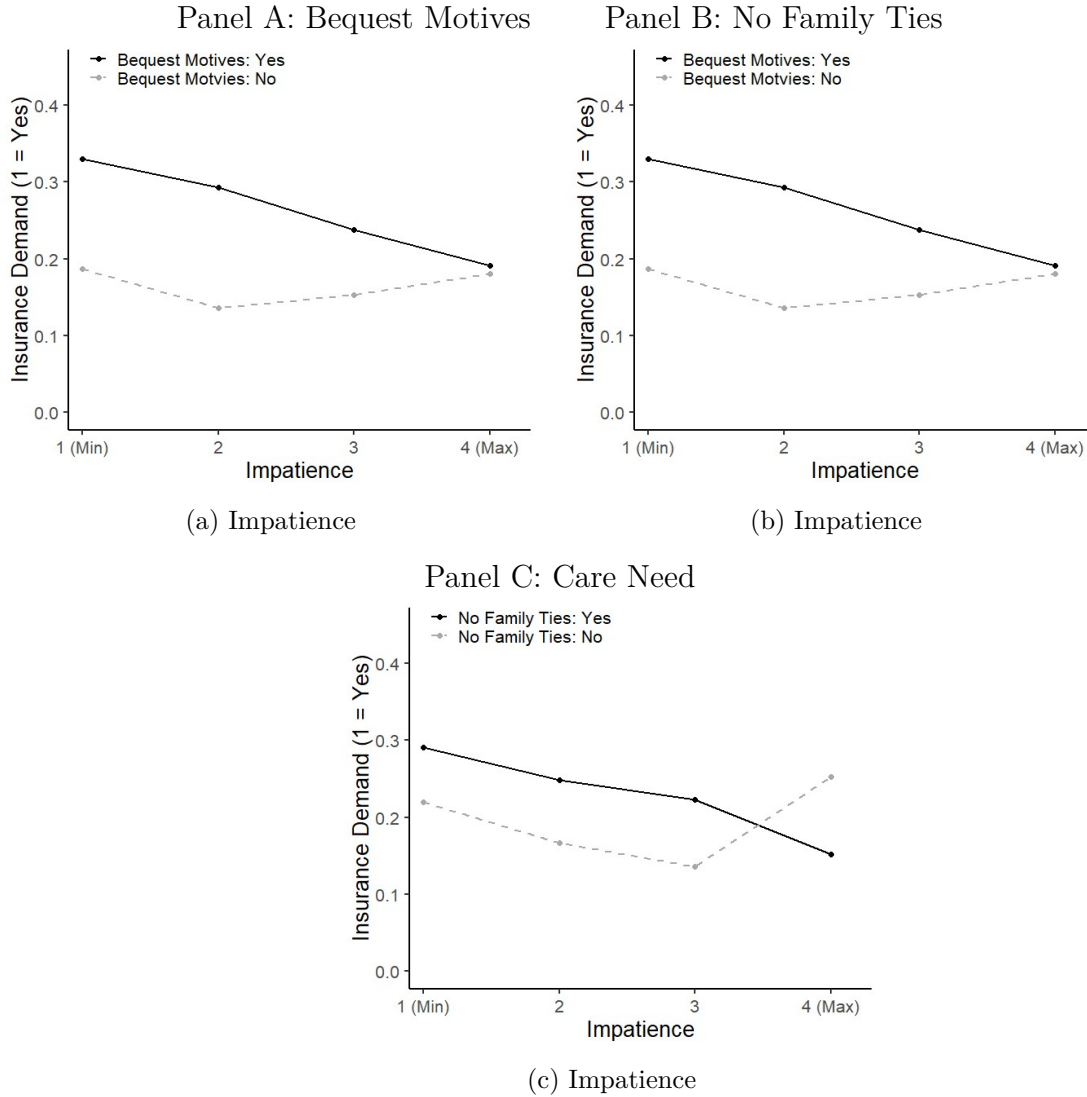


Panel C: Care Need



Note: The figures display average LTC insurance demand rate by risk aversion deciles and ambiguity aversion deciles. The lines distinguish between subjects with weak and strong risk exposure. The three panels employ different risk exposure measures (bequest motives, no family ties, care need).

Figure 2.6: Heterogeneous Effects Attitudes Towards Uncertainty (Risk Exposure)



Note: The figures display average LTC insurance demand rate by the four impatience levels. The lines distinguish between subjects with weak and strong risk exposure. The three panels employ different risk exposure measures (bequest motives, no family ties, care need).

Figure 2.7: Heterogeneous Effects Impatience (Risk Exposure)

family ties, care need). These support the suggestion that, while insurance demand of subjects with strong risk exposure (No Family Ties: Yes, Care Need: Yes) varies sizably with impatience, it is unrelated to risk and ambiguity aversion.

My second auxiliary hypothesis states that the effects of risk aversion, ambiguity aversion, and impatience are stronger for subjects who expect the insurance to perform. The visual inspection displayed in Panel (a) and (b) of Figure 2.8, however, suggest that even among this group (displayed by the solid black line) risk and ambiguity aversion are not systematically related to insurance demand. Panel (c) provides first support for a strong negative effect of impatience among the group of subjects who expect the insurance to perform: demand decreases monotonically from 40% for the most impatient

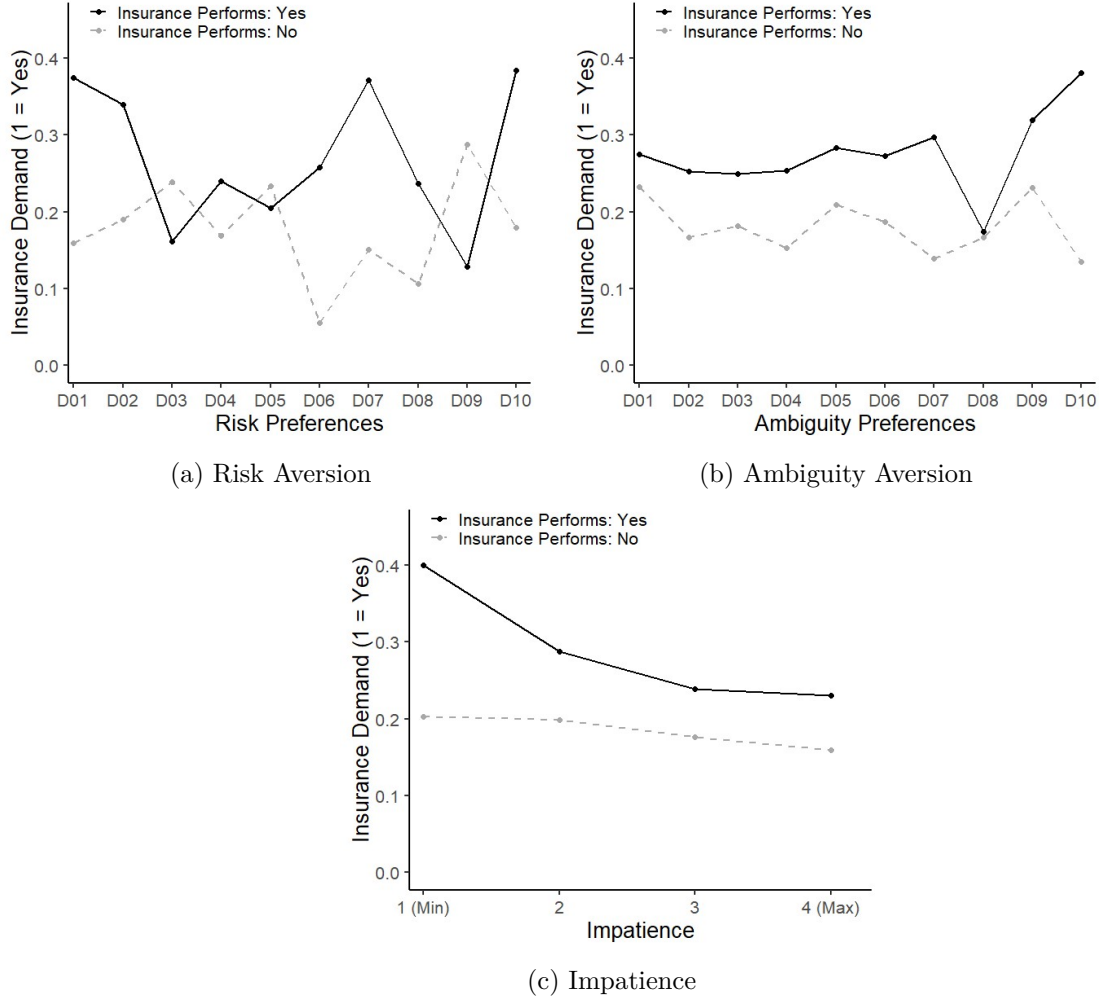


Figure 2.8: Heterogeneous Effects (Insurance Performance)

to 23% for the least impatient. Among the group of subjects who are suspicious that the insurance may not perform, demand seems to be unrelated to impatience.

The suggested effects from this visual inspection are supported by the regressions. Table 2.9 shows univariate and multivariate regression coefficients for risk aversion, ambiguity aversion, and impatience. For each of the mediating variables I first show the results for the group for which I expect more pronounced effects. Panel A shows the coefficients for risk and ambiguity aversion. Almost all of these coefficients are close to 0 and insignificant. The coefficients that are statistically significant go against my hypotheses: For subjects without family ties ambiguity aversion negatively affects insurance demand and for subjects who expect the insurance to perform risk aversion negatively affects insurance demand. Both coefficient are, however, only marginally significant.

Panel B of Table 2.9 shows regression coefficients for impatience. In line with my

hypothesis, the coefficients are in general negative and larger for subjects with strong risk exposure and subjects who expect the insurance to perform. For these subjects most of the univariate regressions coefficients are also statistically significant and economically meaningful. For the first risk exposure measure (Bequest Motives: Yes), for instance, being most impatient reduces insurance demand by 13.9% percentage points (52.5% relative to the mean demand rate of 26.5% in this subsample). The multivariate estimates are weaker in terms of economic magnitude and statistical significance. Here the impatience dummies only remain significant for the group of subjects who expect the insurance to perform. The effect in this group is sizable. A shift from the weakest to the strongest impatience level decreases demand by 14.8 percentage points (54% relative to the mean demand rate of 27.1% in this sample).

2.5.3 Robustness

In accordance with my pre-analysis plan, I conduct a series of robustness tests. All robustness checks support the two key findings that risk and ambiguity preferences do not affect demand for LTC insurance, while impatience has a sizable effect that is most pronounced among subjects with strong risk exposure and subjects who expect the insurance to perform. The regression coefficients of all robustness checks are presented in Section 3.8.1 of the Online Appendix.

In a first set of robustness checks, I show that the results are robust to stricter sampling criteria. To rule out that inattention drives the results, I replicate my analysis on, first, the subsample of subjects who gave consistent answers to two check questions that were embedded in the Dimmock et al. (2016) survey, and, second, on the subsample of subjects who spent at least a total of two minutes on the ambiguity aversion decision tasks in the Dimmock et al. (2016) survey. To rule out the possibility that subjects' financial background drives my result, I limit the sample to subjects reporting that their (family) net wealth (excluding the value of the primary residence) is at least \$10,000. For subjects with net wealth below this threshold, attitudes toward uncertainty and impatience are most likely not a relevant driver for LTC insurance demand decisions. Reasons for this are (i) financing constraints and (ii) that the value of assets is already close to the Medicaid threshold. All of these stricter sampling criteria do not affect my results.

In the second set of robustness checks, I test whether the findings are driven by the

Panel A: Risk and Ambiguity Aversion

		Risk Aversion		Ambiguity Aversion	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.003	-0.013	-0.006	-0.011
	No	-0.016	-0.018	-0.012	-0.005
No Family Ties	Yes	-0.009	-0.017	-0.026*	-0.031*
	No	-0.006	-0.023	0.049*	0.048*
Care Need	Yes	-0.019	-0.028	-0.027	-0.02
	No	-0.001	-0.007	0.07	-0.001
Insurance Performs	Yes	-0.026	-0.045*	0.016	0.012
	No	0.002	0.001	-0.012	-0.018

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.037	-0.093*	-0.139**	-0.025	-0.047	-0.064
	No	-0.051	-0.035	-0.007	-0.068	-0.026	-0.001
No Family Ties	Yes	-0.042	-0.067*	-0.139***	-0.021	-0.011	-0.044
	No	-0.053	-0.084	0.032	-0.023	-0.072	0.05
Care Need	Yes	-0.058	-0.067	-0.072	-0.037	-0.050	0.002
	No	-0.023	-0.062	-0.052	-0.015	-0.082	-0.05
Insurance Performs	Yes	-0.113	-0.161**	-0.17**	-0.124*	-0.131**	-0.148**
	No	-0.005	-0.027	-0.044	-0.002	0.001	0.003

Note: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subjects' demand for LTC insurance. *, **,*** denote significance at the 10-, 5-, and 1-percent level.

Table 2.9: Heterogeneous Effects

specification of the main outcome variable (LTC Insurance Demand). First, I only set the indicator variable to 1 if a subject reports that she holds an LTC insurance policy. Second, I link the survey by Hoffman and Jackson (2013) that asks subjects to state (on a scale from 0 to 100) how likely it is that they will maintain a separate insurance policy for long-term residential health care services in retirement. The results are robust to these alternative specifications of the outcome variable.¹⁸

For the final set of robustness checks I test whether potential results are driven by the specification of the main explanatory variables. For risk and ambiguity aversion I construct an indicator variable (rather than a discrete measure as employed in my main analysis). I then repeat the main analysis with these indicators as my main explanatory variables. For risk preferences I employ a qualitative question on the willingness to take financial risk that was asked in the survey by Yoong et al. (2019). As an alternative measure of time preferences, I employ a qualitative question from the Dimmock et al. (2016) survey addressing the length of the financial planning horizon. Both alternative specifications confirm the results.

2.6 Discussion

In contrast to the hypotheses, the empirical evidence suggest that risk and ambiguity aversion are unrelated to LTC insurance demand. This holds for the full sample and also for subsamples for which I initially expected most pronounced effects (subjects with strong risk exposure and subjects who expect the insurance to perform). While attitudes toward uncertainty do not affect demand, exposure to uncertainty, measured by bequest motives, care need, and no family ties, sizably increases demand. The puzzling co-existence of these findings may result from several potential explanations such as measurement issues relating to risk and ambiguity aversion, consumer's lack of awareness of the financial risk posed by LTC costs, context-dependency of decisions, consumers copying behavior from social peers or following suggestions from financial advisors, and consumers not framing the decision stochastically.

There are at least four arguments that make the first potential explanation (imprecise

¹⁸One may in general be skeptical toward the use of survey responses as outcome variables. However the fact that the demand rate in my sample is (very) close to the rate documented in other studies (e.g. Brown and Finkelstein, 2007; Eling and Ghavibazoo, 2019), provides support for the validity of the survey measure.

measurement of risk and ambiguity aversion) seem implausible. First, as discussed in Section 2.5.3, I can replicate the non-results on the subsample of subjects that are less likely to be subject to measurement error. These are the subsamples of (i) subjects who give consistent answers in check questions, and (ii) subjects who spent a sufficiently large amount of time on the decision tasks. Second, as discussed in Section 2.5.3, I can replicate the non-results if I use a qualitative risk aversion measure.¹⁹ Third, I elicit risk and ambiguity aversion through the survey questions of Dimmock et al. (2016). Using these questions, Dimmock et al. (2016) show that ambiguity aversion helps to explain five portfolio allocation puzzles (non-participation in equities, low allocation to equities, home bias, own-company stock ownership, and underdiversification). In-line with theory, the regression coefficients of risk and ambiguity aversion are statistically significant and economically meaningful. Fourth, my other explanatory variable impatience (capturing time preferences) is also elicited in a (similar) experimental decision task, and here I find statistically significant and economically meaningful effects. It is, thus, unlikely that the non-results of risk and ambiguity aversion are due to imprecise measurements.

A second explanation for the non-results could be the absence of awareness of the risk that potentially high LTC cost pose. Consumers may not be aware that the coverage of Medicare is limited (Brown and Finkelstein, 2009). However, the finding that risk exposure directly affects demand makes this explanation seem implausible. To further rule out this explanation, I repeat my analysis on the subsample of consumers at least 65 years old and of consumers report having close relatives that staid in nursing homes. Risk-awareness should be specifically pronounced among these consumers as they are being covered by Medicare and familiar with LTC homes and its costs. Even in these analyses, the coefficients of risk and ambiguity aversion remain close to 0 and insignificant (see Section 3.8.1 of the Online Appendix for details). This suggests that the absence of awareness of risk cannot explain my non-results for risk and ambiguity aversion.

A third explanation for the non-results is the context-dependency of decisions (e.g. Weber, Blais, and Betz, 2002; Hanoch, Johnson, and Wilke, 2006). The risk and ambiguity aversion measures are elicited in an experimental gamble from a purely financial context. However, the (real-world) decision to demand LTC insurance involves both, the financial risk and health risk. In order to investigate whether context-dependency could

¹⁹Section 3.8.1 of the Online Appendix shows the regression results and also a visual inspection for the effects of the qualitative risk aversion measure.

explain my findings, I link the risk and ambiguity aversion measures to other decisions under uncertainty from a variety of contexts. First, I look at self-employment, investment into further education (move from a bachelor to a master’s degree), routine health checks by a doctor, and real estate ownership. Second, I look at alternative insurance demand decisions (supplementary health insurance, supplementary disability insurance, private life insurance). Third, I look at purely financial decisions. There are stock ownership, conditional stock share (stock value / total financial assets), and individual stock ownership (holding individual stocks not only stock funds). Several empirical studies show that elicited risk aversion measures are typically correlated with these decisions (e.g. Guiso and Paiella, 2008; Hardeweg, Menkhoff, and Waibel, 2013; Falk et al., 2018).²⁰ If my analysis shows that the risk and ambiguity aversion measures employed in this study are mainly correlated with (purely) financial decisions, then this would provide an argument for the explanation that the non-results for LTC insurance are driven by context-dependency. However, as displayed in Table 2.10, even among (purely) financial decisions only a few univariate and multivariate regression coefficients are statistically significant. Additionally, the effect sizes of the significant coefficients are small. Hence, the risk / ambiguity measures employed in this study seem to be less correlated with actual consumer behavior than the measures employed in other studies (e.g. Guiso and Paiella, 2008; Hardeweg, Menkhoff, and Waibel, 2013; Falk et al., 2018).

For one of the robustness checks discussed in Section 2.5.3 I employ subjects’ self-assessed willingness to take financial risk as an alternative (qualitative) risk aversion measure. I also link this measure to the same (additional) decisions under uncertainty. The results are displayed in Table 2.11. This measure also correlates with only a few real-world decisions (stock ownership and individual stock ownership). Considering that all of these are purely financially decisions, this provides some support for the explanation that the non-results for LTC insurance may be due to context-dependency. However, there are at least two arguments that make this explanation look implausible. First, the impatience measure is also elicited in a purely financial context and here I find (strong) effects. Second, studies document that while attitudes toward uncertainty are domain-specific, they are correlated over different domains (Attema, Lharidon, and van de Kuilen, 2019).

²⁰Also note that the finding that elicited preferences do not correlate with real world behavior is not uncommon (e.g. Levitt and List, 2007; Galizzi and Navarro-Martinez, 2019).

	n	Mean	Ambiguity Aversion		Risk Aversion	
			Univariate	Multivariate	Univariate	Multivariate
Self-Employed	776	0.16	0.01	0.004	0.014	0.008
Education	505	0.45	0.006	0.014	-0.008	-0.018
Health Checks	488	0.49	0.056**	0.053**	0.032	0.025
Home Owner	1107	0.83	0.012	-0.001	0.005	-0.001
Private Health Ins.	1063	0.16	-0.007	0	-0.016	-0.019
Private Disab. Ins.	1063	0.06	0.005	-0.002	0.008	0.008
Private Life Ins.	1063	0.57	0.002	-0.018	0	0.003
Has Stocks	1103	0.39	0.027*	0.009	-0.003	-0.009
Stock Share	408	0.56	-0.017	-0.003	-0.018	-0.015
Individual Stocks	420	0.66	-0.062**	-0.071**	0.012	0.031

Note: The table shows sample size, the mean dependent variable, as well as univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion. *, **, *** denote significance at the 10-, 5-, and 1-percent level. The specification of the multivariate regression model is inspired by Guiso and Paiella (2008) and includes controls for age, gender, family size, income, wealth, education, health, and financial literacy.

Table 2.10: Average Effects for Alternative Outcomes

	n	Mean	Univariate		Multivariate	
			Medium	Strong	Medium	Strong
Self-Employed	776	0.16	-0.014	-0.040	-0.021	-0.060
Education	505	0.45	0.077	0.054	0.084	0.095
Health Checks	488	0.49	-0.033	-0.117	0.011	-0.059
Home Owner	1107	0.83	0.042	-0.105	0.029	-0.019
Private Health Ins.	1063	0.16	0.004	-0.008	-0.018	-0.035
Private Disab. Ins.	1063	0.06	-0.039	-0.055	-0.032	-0.021
Private Life Ins.	1063	0.57	-0.027	-0.072	-0.006	0.007
Has Stocks	1103	0.39	-0.026	-0.328***	-0.042	-0.235***
Stock Share	408	0.56	0.014	-0.011	0.019	-0.014
Individual Stocks	420	0.66	-0.121*	-0.330***	-0.119**	-0.283**

Note: The table shows sample size, the mean dependent variable, as well as univariate and multivariate regression coefficients for the qualitative risk aversion measure. *, **, *** denote significance at the 10-, 5-, and 1-percent level. The specification of the multivariate regression model is inspired by Guiso and Paiella (2008) and includes controls for: age, gender, family size, income, wealth, education, health, and financial literacy.

Table 2.11: Average Effects Qualitative Risk Aversion Measures (Alternative Outcomes)

A fourth potential explanation for the co-existence of a strong exposure to uncertainty effect and non-results of attitudes toward uncertainty could be that many consumers copy decisions from social peers, or follow suggestions from financial advisors when making important real-world financial decisions. According to the study by Egan, Matvos, and Seru (2019), 56% of the U.S. consumers ask for advice from financial professionals. Additionally, a large body of research documents peer effects in risk taking (e.g. Shiller, Fischer, and Friedman, 1984; Lahno and Serra-Garcia, 2015). However, at least two arguments make the potential explanation that the results of this study are mainly driven by social peers or financial advisors look implausible. First, consumers' impatience (strongly) affects LTC demand. Second, the qualitative risk aversion measure (see Table 2.11) and also the quantitative ambiguity aversion measure (see Table 2.10) correlate with (at least some) other financial decisions. It is unlikely that consumers fully depend on social peers and financial advice in the LTC insurance context, but make independent decisions in other complex financial contexts (e.g. the decisions on how to diversify the stock portfolio).

A fifth potential explanation for the findings of this study is that consumers do not view LTC as a stochastic problem. Instead, LTC is determined by risk exposure. Consumers with only weak risk exposure expect that they (with certainty) will not require care, whereas consumers with (strong) risk exposure expect that they will require LTC. Additionally, because expectations about care costs vary (e.g. Hoffman and Jackson, 2013), not every consumer that expects to require care actually demands LTC insurance. While the assumption that consumers view LTC as a deterministic rather than a stochastic situation is strict, this could explain why exposure to uncertainty matters, but the extent to which this affects LTCI demand does not vary with consumers' attitudes toward uncertainty. However, following the same argument, the regression coefficients displayed in Table 2.10 and Table 2.11, would then suggest that consumers also view other insurance settings (health, disability, life) as non-stochastic. Hence, also this explanation seems to be at least questionable.

Each of the five potential explanations discussed above seems implausible to some extent. It is, thus, unlikely that one explanation by itself provides a sufficient explanation. Hence, it is more likely that either a combination of those explanations, or a so far neglected aspect provides an answer for why exposure to uncertainty, i.e. bequest motives,

no family ties, beliefs about care need, matters, whereas attitudes toward uncertainty do not affect demand. Considering that this study can not provide a clear answer to this questions, this provides an interesting revenue for further research projects.²¹

2.7 Conclusion

This pre-registered study investigates the role of attitudes toward uncertainty (risk and ambiguity) and time preferences (impatience) for the demand of LTC insurance. Linking three surveys that were conducted on a sample representative of the U.S. population in 2011 - 2012, I find that attitudes toward uncertainty are unrelated to LTC insurance demand, even among subjects with strong risk exposure and subjects who expect the insurance to perform. In contrast, time preferences (impatience) matter. The effect of impatience is most pronounced among subjects with strong risk exposure and subjects who expect the insurance to perform. Within these groups, impatient subjects are 15 percent points less likely to demand insurance than their patient counterparts.

While attitudes toward uncertainty are unrelated to LTC insurance demand, perceived exposure to uncertainty (beliefs about risk exposure and beliefs about performance of the insurance) has a sizable effect. Similar to the effects documented by Brown, Goda, and McGarry (2012), I find that subjects with strong risk exposure and subjects who expect the insurance to perform are roughly 10 percentage points more likely to demand LTC insurance. Given the low demand for LTC insurance (<20%) and its considerable welfare effects, potential policy interventions should provide consumers with salient information on their risk exposure and limit the actual and the perceived counterparty risk. Table 2.12 simulates the potential consequences of such an intervention with data from my sample. The table shows how the demand rate increases from the baseline (full sample) to the subsample of consumers who are (i) aware of the strong risk exposure, and (ii) expect the insurance to perform (Subsample VII). It shows that in case consumers are aware of the risk and they expect the insurance to perform, insurance demand could be increased to roughly 40%. This is close to doubling the baseline demand rate.

²¹Recent evidence suggests that risk aversion, ambiguity aversion, and impatience are not just context- but also domain-dependent (preferences differ between the gain or loss domain; e.g. Kocher, Lahno, and Trautmann, 2018). Considering that the decision to demand insurance is often viewed as a decision in the loss domain (e.g. Sydnor, 2010), further research could, for instance, elicit these preferences in the loss domain and link them to LTC insurance demand.

As my findings document, limited demand for LTC insurance results at least partially from consumers' time preferences. Demand of impatient consumers remains low even if they are aware of their risk exposure and expect the insurance to perform. Importantly, the same consumers, i.e. the most impatient ones, are also less likely to save up a large financial buffer (e.g. Epper et al., 2020). Hence, the impatient consumers are most vulnerable to LTC expenditure shocks. The recent study by Goda et al. (2019) highlights that non-standard time preferences (present biasedness) have a further (independent) negative impact on (retirement) savings. Policy interventions targeting standard time preferences (impatience) and also non-standard time preferences (present bias) should therefore be viewed as a crucial element for improving the private preparation for LTC expenditure risks.

Sample	Ins. Perf.: Yes	Beq. Mot.: Yes	Care Need: Yes	n	Mean Demand
Full Sample				1109	0.22
Subsample I	x			401	0.26
Subsample II		x		572	0.27
Subsample III			x	482	0.27
Subsample IV	x	x		214	0.32
Subsample V	x		x	138	0.37
Subsample VI		x	x	276	0.31
Subsample VII	x	x	x	92	0.37

Note: The table shows the mean insurance demand in different subsamples. An "x" denotes that a mediating variable is set to "Yes". The first subsample (Subsample I), for instance, consists of the subjects for whom the insurance performance variable is set to "Yes". Among this group the demand rate is 0.27.

Table 2.12: Simulation of Demand Rates

Chapter 3

Intertemporal Prospects Theory

Immanuel Lampe & Matthias Weber

Abstract

Prospect Theory is the most prominent contender of expected utility theory to describe decisions under risk. In atemporal contexts, prospect theory is well understood. In intertemporal contexts, however, it is not clear how prospect theory should be applied (in particular, whether probabilities should be weighted within time periods or whether the probabilities of present values should be weighted). It is also unclear what parametric specifications of probability-weighting and value functions should be used. We find in a pre-registered experiment on a representative sample that an application of prospect theory weighting probabilities of present values predicts decisions best. Estimated probability weighting functions are very similar to those typically estimated in atemporal settings, while value functions are almost linear with a loss aversion coefficient close to one.

3.1 Introduction

Analyzing decisions under risk is an important topic in research in economics, finance, and business. The most prominent contender of expected utility theory is (cumulative) prospect theory (Tversky and Kahneman, 1992). Prospect theory entails two fundamental breakaways from the classical expected utility model. First, instead of defining preferences over total wealth, preferences are defined over changes with respect to a reference point, and it is assumed that negative changes (losses) are treated differently than positive changes (gains). Second, outcomes are not weighted by objective probabilities but rather by transformed probabilities (specifically, unlikely large gains and unlikely large losses are overweighted). Considering financial decisions, prospect theory can, for example, explain the equity premium puzzle (Benartzi and Thaler, 1995; Barberis and Huang, 2006), the stock market participation puzzle (Dimmock and Kouwenberg, 2010), and the disposition effect (Odean, 1998; Weber and Camerer, 1998; Barberis and Xiong, 2009; Meng and Weng, 2017). In other fields of economics, prospect theory can explain the downward-sloping labour supply curve (Goette, Huffman, and Fehr, 2004), the avoidance of probabilistic insurance (Wakker, Thaler, and Tversky, 1997), and the choice of deductible in insurance contracts (Sydnor, 2010). DellaVigna (2009) and Barberis (2013) provide overviews of many more phenomena that are inconsistent with expected utility theory but can be explained with prospect theory.

Most applications of prospect theory assume an atemporal setting, that is, a setting where the gains and losses materialize at one point in time (e.g., Benartzi and Thaler, 1995; Berkelaar, Kouwenberg, and Post, 2004; Gomes, 2005; and Barberis and Huang, 2006). In these settings, prospect theory has been thoroughly analyzed and is well understood. Many natural settings, however, involve gains and losses at different points in time. Recent studies integrate elements of prospect theory in such intertemporal settings (see for example Barberis and Huang, 2009; Barberis and Xiong, 2009; De Giorgi and Legg, 2012; van Bilsen, Laeven, and Nijman, 2020; Hlouskova, Fortin, and Tsigaris, 2017; Meng and Weng, 2017; Deng and Pirvu, 2019). However, in intertemporal applications, usually only some aspects of prospect theory are incorporated into a setting that is otherwise one of discounted expected utility maximization. A majority of these studies include loss aversion with respect to a reference point in their models as in prospect theory but neglect probability weighting (e.g., Kyle, Ou-Yang, and Xiong, 2006; Barberis and Huang, 2009;

Barberis and Xiong, 2009; Henderson, 2012; Easley and Yang, 2015; Hlouskova, Fortin, and Tsigaris, 2017; Meng and Weng, 2017).

To date, there is no generally accepted version of prospect theory in intertemporal settings. There are not only minor disagreements about the calibration of the parameters, but there is not even agreement on how probability weighting should be applied. Considering that prospect theory is widely viewed as the most accurate available description of how people make risky decisions, this is surprising. This research project addresses this gap in the literature and aims to provide guidance on how prospect theory should best be applied to intertemporal settings.

We refer to the first possible method that can be used as the time-separation method. With this method, outcomes are ranked within each period and decision weights are calculated (with probability weighting functions similar to an atemporal setting). Given these decision weights, each period's PT value can be calculated and the overall PT value is then the time-discounted sum of these values. Note that the time discounting need not be exponential, any other form of discounting such as hyperbolic or quasi-hyperbolic discounting may also be used. This first method of applying prospect theory is, for instance, assumed in the analyses by Andreoni and Sprenger (2012); De Giorgi and Legg (2012); Guo and He (2017); Krause, Ring, and Schmidt (2020) and van Bilsen and Laeven (2020).

The second method, which we refer to as the present-value method, first calculates the decision maker's present value of each possible stream of outcomes, in utility terms (with a given form of time discounting). These present values are then ranked and their decision weights are calculated (decision weights are again calculated analogously to atemporal prospect theory). The overall PT value is then calculated as the atemporal PT value of the present values. This method (or a version of it with rank-dependent utility, not distinguishing between gains and losses but including probability weighting) is used in the studies by Chew and Epstein (1990), Bleichrodt and Eeckhoudt (2006), Halevy (2008), Drouhin (2015), Epper and Fehr-Duda (2015), Blavatskyy (2016), Andreoni, Feldman, and Sprenger (2017), and Andersen et al. (2018).

In general, the two methods yield different results. For studies that neglect probability weighting, both methods predict the same evaluation of prospects, however. The first step towards providing a unifying standard of how to apply prospect theory in intertemporal

settings is to choose between these two methods.

A second open issue when moving from atemporal to intertemporal prospect theory is the specification of the value and probability weighting functions (for a given method of applying prospect theory). Many studies that integrate elements of prospect theory into intertemporal models use functional forms and parameter calibrations obtained in atemporal settings.¹ It is a priori not clear that the specifications of the utility and probability weighting functions obtained in an atemporal setting are well suited to analyze intertemporal choices. The studies by Abdellaoui, l’Haridon, and Paraschiv (2013) and Abdellaoui et al. (2013), for instance, suggest that the utility function in intertemporal contexts is close to linear for gains and losses and that the loss aversion parameter is smaller than usually found in atemporal contexts (elicited in intertemporal settings without risk).

In this study, we elicit certainty equivalents of intertemporal lotteries in a representative population. We estimate parameter calibrations for a variety of different value, probability-weighting and time-discount functions and can then determine which of the two methods describes risky choices best. We also provide a benchmark of functions and parameter values for intertemporal applications. For a full specification of intertemporal prospect theory, we estimate value and probability-weighting functions jointly with the method of time discounting.²

Very closely related literature is scarce. Epper and Fehr-Duda (2015) nicely illustrate the co-existence of the two methods of intertemporal prospect theory and show that the present-value method can explain a decision pattern that cannot be explained with the time-separation method (documented in Andreoni and Sprenger, 2012). However, their study does not attempt to establish which method in general predicts choices better (neither to estimate utility, probability-weighting, or time-discount functions).

The two existing studies that attempt to analyze which of the two methods of prospect theory explains human choices better provide conflicting evidence. Andreoni, Feldman, and Sprenger (2017) find support for the time-separation method, while Rohde and Yu

¹Many studies use the specifications of Tversky and Kahneman (1992), who provide a natural benchmark, despite the fact that specifications obtained in larger representative samples are available, (e.g., Booi, Van Praag, and Van De Kuilen, 2010). Note, however, that the parameters obtained are generally similar to those provided by Tversky and Kahneman (1992).

²In our experiment, we implement very salient reference points of zero in the different periods. In later applications, it will of course be possible to work with different reference points.

(2022) find support for the present-value method. Both studies rely on experimental designs that make the observations of certain outcomes more or less likely depending on whether experimental subjects use the time-separation method or the present-value method. Andreoni, Feldman, and Sprenger (2017) investigate whether adding an independent common future risk affects the choice between two lotteries. Assuming functional forms as usually found in atemporal settings, the choice can change if participants use the present-value method to evaluate the lotteries but not if they use the time-separation method (because the PT value of the newly added time period is identical for both lotteries). Andreoni, Feldman, and Sprenger (2017) interpret their findings as support for the time-separation method. The support for this interpretation is not very strong, however, because choices do change in roughly 50% and the difference in explanatory power between the methods is small.³ Rohde and Yu (2022) investigate intertemporal correlation aversion in a laboratory experiment (in a study conducted at the same time as ours and independently of it). Intertemporal correlation aversion can arise if participants use the present-value method to evaluate the lotteries but not if they use the time-separation method. Rohde and Yu (2022) find that the majority of participants is averse to intertemporal correlation, their results thus lend support to the present-value method.

Our paper differs decisively from Andreoni, Feldman, and Sprenger (2017) and Rohde and Yu (2022). Rather than presenting participants combinations of simple lotteries, where certain choices by participants are in line with one method or the other, we attempt to establish which application method has higher predictive power when participants evaluate many lotteries (in a setting that does not favor any of the two methods a priori). We also believe that thoroughly estimated value, probability-weighting, and time-discount functions in an intertemporal setting are of high value. Scholars and practitioners can only use the different methods in applications if such a parametrization is available (estimating the parameters anew also seems necessary to make sure that the comparison between the methods is not driven by potentially unfitting atemporal calibrations). To be able to obtain parameters that extend beyond a typical student sample (as used, for instance, in Andreoni, Feldman, and Sprenger, 2017, and Rohde and Yu, 2022), we conduct the

³Furthermore, Andreoni, Feldman, and Sprenger (2017) present the relevant choice lists (that only differ by the same added outcome of a 90% or 10% chance of 19 or 9 USD in four weeks) one after another to the same participants. This nudges people to make a consistent choice, which favors the time-separation method in their setup.

study on a representative sample.⁴

To preview our results, the present-value method predicts observed choices significantly better than the time-separation method for all considered parametric specifications. The prediction performance is also much better than the prediction performance of expected discounted utility models. The estimated value functions are almost linear for gains and losses and have a loss aversion coefficient close to one. The estimated probability-weighting functions are inverse-S shaped and very similar to typical atemporal calibrations.

While our main focus lies on the comparison of the time-separation method and the present-value method, we also compare these methods to a third application method, which is similar to the present-value method. This method also calculates the present values of outcome streams first, but it calculates these present values in monetary terms before entering them in a value/utility function (in contrast to the regular present value method, which calculates present values directly in utility terms). The third application method based on present values in monetary terms performs as well as the regular present-value method.

As a minor additional result, there is no noticeable difference between incentivized and hypothetical choices in our experiment. This is not surprising, given that the valuation of lotteries does not contain strategic elements or social- or self-image considerations. This is in line with the literature (e.g., Abdellaoui, l’Haridon, and Paraschiv, 2011; Brañas Garza et al., 2020; Hackethal et al., 2020).

This paper is organized as follows. Section 3.2 introduces the two methods of applying prospect theory to intertemporal settings. Section 3.3 contains the experimental design and briefly discusses the pre-registration and the experimental procedures. Section 3.4 discusses parametric specifications, the estimation method, and the measure of prediction performance. Section 3.5 shows the results. Section 3.6 presents parameter calibrations that we recommend for intertemporal applications and concludes.

⁴There are additional differences, in particular when compared to Andreoni, Feldman, and Sprenger (2017). Participants’ choices in Andreoni, Feldman, and Sprenger (2017), for instance, only influence the first periods’ payouts; that is, what happens in the future is independent of participants’ choices. This runs counter to many natural settings in which current decisions also influence the distribution of future risks (e.g., investments, education, health), and, in particular, it means that there is no possibility for ‘diversification across time’, which Epper and Fehr-Duda (2015) consider an important reason why the present-value method may explain peoples’ choices better. In our experiment, future risks are in general not independent.

3.2 Modeling Options for Intertemporal Prospects

This section introduces intertemporal prospects and the two (main) possibilities of modeling intertemporal decisions with prospect theory.

3.2.1 Intertemporal Prospects

An atemporal prospect yields one single payout at one time period. Figure 3.1 a) displays an explanatory atemporal prospect. The three potential outcomes (arriving at $t = 0$, without time discounting) are labeled z_1, z_2 and z_3 . Outcome z_1 , for instance, arrives with probability p_1 .

An intertemporal prospect may yield payouts at different time periods. Figure 3.1 b) displays an explanatory intertemporal prospect. The potential outcomes of period t are labeled by $z_{t,1}, z_{t,2}, \dots$. A period's outcomes are not necessarily distinct (that is, $z_{1,2} = z_{1,3}$ in Figure 3.1, for instance, is possible) and the labels may not reflect the outcomes' rank-order. In the first period ($t = 0$), either outcome $z_{0,1}$ arrives (with probability p) or outcome $z_{0,2}$ (with probability $1 - p$). Outcomes at $t = 1$ and $t = 2$ depend in general on the outcomes of previous periods. The probability that one specific outcome arrives is, thus, equal to the product of its path probabilities. The probability that the outcome at $t = 1$ equals $z_{1,1}$ is, for instance, given by $p \cdot q$.

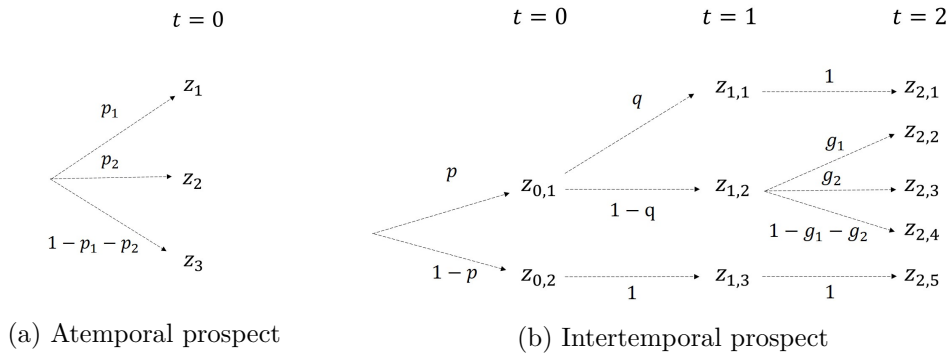


Figure 3.1: Examples of an atemporal and an intertemporal prospect

3.2.2 Time-separation Method

To evaluate a prospect with outcomes in T periods, the time-separation method first calculates each period's PT value. These values are then time-discounted and added up, with a given time-discount function δ (generally with $\delta(0) = 1$). We denote the PT value

of period t by V_t , $t = 0, \dots, T - 1$. Applying the time-separation method to the example prospect of Figure 3.1 implies that its PT value is the sum of its three time-discounted PT values, as illustrated in Figure 3.2.

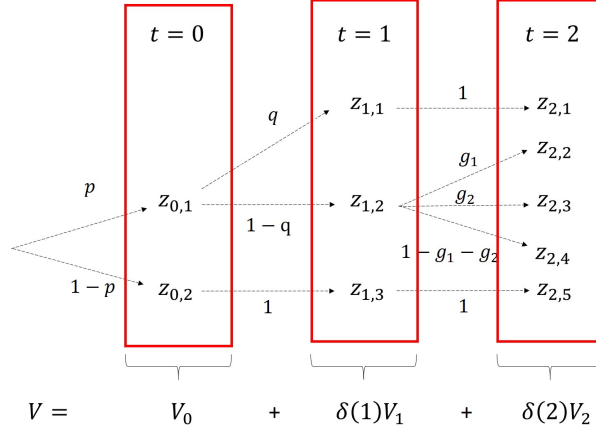


Figure 3.2: Illustration of the time-separation method

To calculate each period's PT value, prospect theory is applied as in an atemporal setting. Periods' outcomes are ranked and their objective probabilities are transformed into subjective decision weights. Denote by $x_{t,1}, \dots, x_{t,n_t}$ the ordered and distinct outcomes of period t and by $p_{t,1}, \dots, p_{t,n_t}$ their objective probabilities. Each period's outcome set may consist of gains and losses, so that $x_{t,1} > x_{t,2} > \dots > x_{t,k_t} > 0 > x_{t,k_t+1} > \dots > x_{t,n_t}$. Note that the objective probabilities are compound probabilities (for example, if $z_{1,1} > z_{1,2}$ and $z_{1,1} > z_{1,3}$ in Figures 3.1 b) and 3.2, then $x_{1,1} = z_{1,1}$ and $p_{1,1} = p \cdot q$). The PT value of period t can then simply be calculated with the formula

$$V_t = \sum_{i=1}^{k_t} \pi_{t,i}^+ v(x_{t,i}) + \sum_{l=k_t+1}^{n_t} \pi_{t,l}^- v(x_{t,l}),$$

with v denoting the decision maker's value function (i.e., the utility function), which is strictly increasing. We assume that the reference point is at 0 and $v(0) = 0$. Further, the decision weights $\pi_{t,i}^+$ and $\pi_{t,i}^-$ are defined by

$$\begin{aligned} \pi_{t,1}^+ &= w^+(p_{t,1}), \quad \pi_{t,n_t}^- = w^-(p_{t,n_t}), \\ \pi_{t,i}^+ &= w^+(p_{t,1} + \dots + p_{t,i}) - w^+(p_{t,1} + \dots + p_{t,i-1}), \quad \text{for } 1 < i \leq k_t, \\ \pi_{t,l}^- &= w^-(p_{t,l} + \dots + p_{t,n_t}) - w^-(p_{t,l+1} + \dots + p_{t,n_t}), \quad \text{for } k_t < l < n_t. \end{aligned}$$

Here w^+ is the probability weighting function for gains and w^- that for losses, satisfying

$w^+(0) = w^-(0) = 0$, $w^+(1) = w^-(1) = 1$, both monotonically increasing.

The overall value of the prospect, which we label V , is then the sum of all time-discounted PT values, thus $V = \sum_{t=0}^{T-1} \delta(t) V_t$.

3.2.3 Present-value Method

The present-value method evaluates an intertemporal prospect by calculating the present values of the possible streams of outcomes in utility terms, and then weighting the probabilities of these present values. A stream of outcomes, is a sequence of outcomes that arrives with positive probability. We denote the different possible streams of outcomes by $o_1, o_2, \dots$. An outcome stream o_j thus consists of T outcomes, one in each time period, $o_j = (o_{j,0}, \dots, o_{j,T-1})$, with $o_{j,t}$ denoting the outcome in period t . Figure 3.3 illustrates the outcome streams of the example given in Figure 3.1 (for o_2 , for instance, $o_{2,0} = z_{0,1}$, $o_{2,1} = z_{1,2}$, and $o_{2,2} = z_{2,2}$).

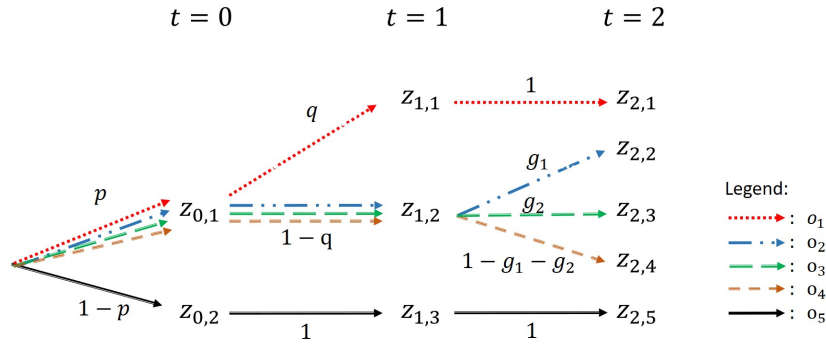


Figure 3.3: Illustration of the present-value method

The present value of outcome stream o_j , in utility terms, is given by $PV(o_j) = \sum_{t=0}^{T-1} \delta(t) v(o_{j,t})$. The present value of outcome stream o_1 in Figure 3.3 is, for instance, given by $v(z_{0,1}) + \delta(1)v(z_{1,1}) + \delta(2)v(z_{2,1})$, with $\delta(0) = 1$ as usually. We denote the number of distinct present values by m and rank-order them, so that $PV_1 > \dots > PV_k > 0 > PV_{k+1} > \dots > PV_m$. The probability of receiving the outcome stream with present value PV_j is denoted by q_j .

The overall value of the intertemporal prospect, W , is the sum of all present values multiplied by their decision weights as in atemporal prospect theory,

$$W = \sum_{j=1}^k \pi_j^+ PV_j + \sum_{h=k+1}^m \pi_h^- PV_h,$$

with the decision weights for gains and losses defined by

$$\begin{aligned}\pi_1^+ &= w^+(q_1) , \pi_m^- = w^-(q_m), \\ \pi_j^+ &= w^+(q_1 + \dots + q_j) - w^+(q_1 + \dots + q_{j-1}), \text{ for } 1 < j \leq k, \\ \pi_h^- &= w^-(q_h + \dots + q_m) - w^-(q_{h+1} + \dots + q_m), \text{ for } k < h < m.\end{aligned}$$

3.2.4 Differences in Evaluations

In general, both application methods yield different evaluations of prospects, assuming non-linear weighting of probabilities (with linear weighting, both methods always yield the same evaluation). However, for a subset of lotteries, both methods give the same PT value. Specifically, the methods give the same PT value for a lottery if any outcome stream of the lottery contains only non-negative or non-positive outcomes and if, in addition, the lottery possesses a property that we call rank-order stability. We provide a formal definition in Appendix 3.9 and a proof that lotteries with these properties are indeed evaluated equally. Intuitively, rank-order stability means that if one outcome is larger than another outcome within one period, then, for any other period, the outcomes that may arrive in addition to the larger outcome (i.e., outcomes that are in one of the outcome streams containing this larger outcome) must be at least as large as the outcomes that may arrive in addition to the smaller outcome. Rank-order stability therefore implies that the best outcome stream bundles the best outcomes of each period.

Figure 3.4 displays two explanatory prospect. Both prospects contain only non-negative payouts. The first prospect is rank-order stable and its evaluation is, thus, identical for both application methods. The second prospect is not rank order stable. An arrival of the good outcome 60 at $t = 0$ can be followed by the arrival of 0 at $t = 1$, whereas the arrival of the outcome 0 at $t = 0$ can be followed by the arrival of 60 at $t = 1$.

For most economic or financial applications the evaluations between the methods will differ. For instance, if a good outcome in one period can be followed by a bad outcome in another period, rank-order stability does not hold. In addition, even if rank-order stability holds, the evaluations can differ if some outcome streams contain both positive and negative outcomes.

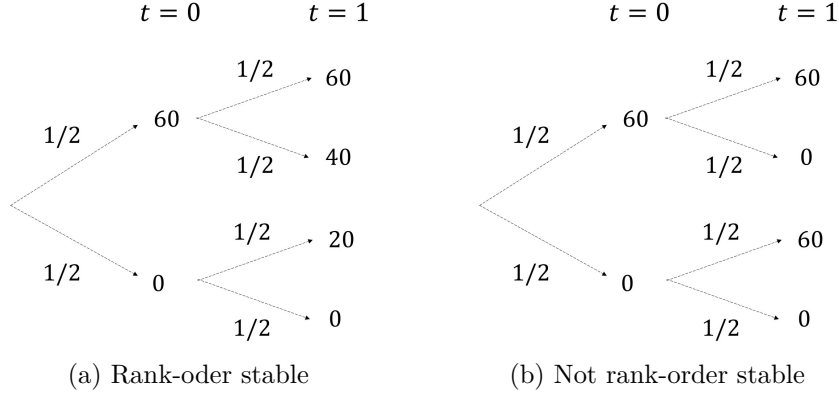


Figure 3.4: Rank Order Stability (Examples)

Notes: This figure shows two examples of intertemporal prospects, one which is rank-order stable and one which is not rank-order stable.

3.3 Experimental Design and Procedures

3.3.1 Decision Tasks

Each subject makes 48 decisions. For each decision, a subject is presented a lottery (framed neutrally as a risky option) with a time horizon of three periods ($t = 0, 1, 2$). The first period ($t = 0$) refers to the time of the experiment, the second period ($t = 1$) to three months after the experiment, and the third period ($t = 2$) to six months after the experiment. 16 of the lotteries only contain positive outcomes (gain lotteries), 16 only contain negative outcomes (loss lotteries), and 16 contain positive and negative outcomes (mixed lotteries).

For each lottery, we elicit a subject's switching point from the lottery to a safe option that yields three certain and identical payouts, the first received at the time of the experiment, the second three months later, and the third six months later. We elicit the switching point by asking subjects to position a slider that indicates for which payout amounts of the lottery they prefer the lottery over the safe option (and, vice versa, for which payout amounts of the lottery they prefer the safe option).

Figure 3.5 shows an example of such a decision task. At the top, subjects see the intertemporal lottery of this decision task (with non-trivial probabilities illustrated with a wheel of fortune). Below that, subjects see an illustration of the safe option (without the monetary values filled in, because these depend on subjects' choices in the task). Below that, subjects see a short description of the meaning of the position of the slider

and the slider which they can position. When subjects move the slider (which is initially always positioned at the leftmost position) they increase the amount that they need to be offered in the safe option (three times) in order to prefer the safe option over the lottery. The bold numbers in the row above the slider change when the slider is moved. The difference between these two bold numbers is always one euro (in the analysis, we take the midpoint between these two number as the certainty equivalent).⁵

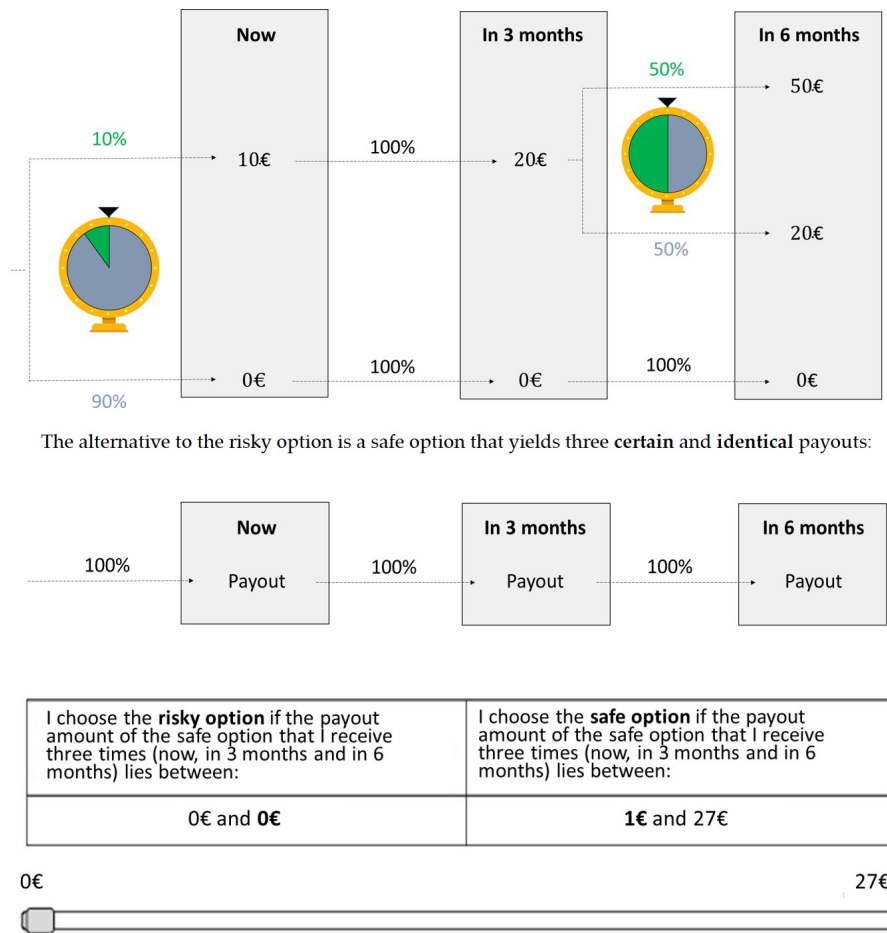


Figure 3.5: Example of a decision task

Notes: This figure shows a decision task. On top is the decision task's intertemporal lottery, followed by an illustration of the safe option (without payout values). The bottom part shows a description of the slider and the slider to elicit the certainty equivalent of the intertemporal lottery.

⁵The limits of the slider (i.e., the leftmost and rightmost positions) are the minimal possible sum of payouts across the three time periods (without time discounting) of the intertemporal lottery in the decision task and the maximal possible sum of payouts.

3.3.2 Lotteries

All lotteries used in the experiment, with a description of why they have been chosen, can be found in Appendix 3.9. Here, we describe the structure behind the lottery choices more generally and show a few examples.

The following design features hold for all lotteries and aim at keeping the experiment comprehensible for participants: (1) each branching in the trees describing the intertemporal lotteries leads to at most two distinct outcomes in the following period; (2) in the last period, the number of distinct outcomes is limited to four (this is achieved by relying on outcomes that arrive with probability one in one time period); (3) outcomes appear only with probabilities 1, 9/10, 2/3, 1/2, 1/3, or 1/10.

The 48 lotteries of the experiment can be categorized in 6 sets, each containing 8 lotteries. The first 3 sets consist of low-stake lotteries: low-stake gain lotteries (Set 1), low-stake loss lotteries (Set 2), and low-stake mixed lotteries (Set 3). The other three sets consist of high-stake gain lotteries (Set 4), high-stake loss lotteries (Set 5), and high stake mixed lotteries (Set 6). The sets are summarized in Table 3.1. The different sets appear in random order. Lotteries within each set similarly appear in random order.

	Gains	Losses	Gains & Losses
Low stakes	Set 1	Set 2	Set 3
High stakes	Set 4	Set 5	Set 6

Table 3.1: Overview lottery sets

In general, the loss lotteries (Sets 2 and 5) can be obtained by multiplying all outcomes of the gain lotteries (Sets 1 and 4) by -1 . The high-stake lotteries (Sets 4 to 6) can be obtained by multiplying the low-stake lotteries (Sets 1 to 3) by 20. The 8 lotteries of each set consist of 6 calibration and 2 test lotteries, implying a total of 36 calibration and 12 test lotteries. Below we provide further information on the calibration and test lotteries.

Calibration Lotteries: We use the certainty equivalents reported for the calibration lotteries to estimate the parameters of value function, weighting functions, and time-discount function jointly. The calibration lotteries of the sets ensure that all functions can be estimated on a relatively dense grid, for the value functions including small, intermediate and large positive and negative values.

The outcome streams of the calibration lotteries contain only non-negative or non-

positive outcomes and the calibration lotteries are rank-order-stable. As explained in Section 3.2.4, this implies that for any given combination of value function, probability-weighting functions, and time-discount function, the evaluations under the time-separation method and the present-value method are identical. The parameter estimates obtained on the calibration lotteries are, thus, the same for both methods.

Figure 3.6 shows two explanatory calibration lotteries from Set 1 (low-stake gain lotteries). All outcomes are in euros. The outcome of Lottery 1 at $t = 0$ is either 10 with a low probability or 0 with a high probability. An arrival of the good outcome at $t = 0$ implies the arrival of good outcomes at $t = 1$ (20 with certainty as compared to 10 with certainty) and also at $t = 2$ (50 and 20 equally likely, compared to 0 with certainty). Lottery 1, hence, contains several unlikely good outcomes. Lottery 3, in contrast, contains several likely good outcomes. The variation in outcomes contributes to the value function being estimated on several small positive values. Similarly the variation in good outcomes' arrival probabilities contributes to the probability weighting function for gains being estimated on several values on the interval $[0, 1]$.

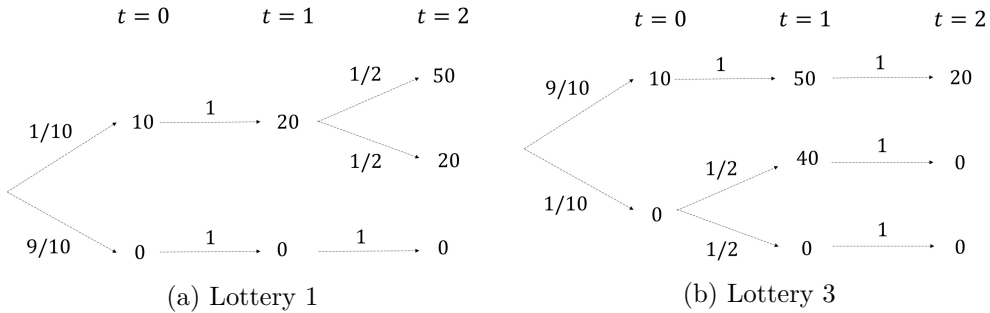


Figure 3.6: Calibration lottery examples, Lottery Set 1 (low-stake gain lotteries)

Test Lotteries: The test lotteries are designed such that the evaluations under the two methods give (sizably) different results. The test lotteries can therefore be used to compare the out-of-sample explanatory power of the two methods. In each of the six sets, one of the two test lotteries is chosen such that the time-separation method leads to a higher (multi-period) certainty equivalent than linear probability weighting if parameters are similar to the ones usually found for atemporal prospect theory, while the present-value method leads to a lower certainty equivalent. The opposite holds for the other test lottery. In order to assure a fair comparison between the two methods we choose the test lotteries such that the degree to which one method over- and the other method

undervalues the lottery are similar (assuming typical atemporal calibrations).

Figure 3.7 shows the two test lotteries from Set 6 (high-stake mixed lotteries). In Lottery 47, the time-separation method would simultaneously underweight the most negative outcome at $t = 1$ (-600 arrives with probability $1/2$) and overweight the most positive outcome at $t = 2$ (1200 arrives with probability $1/6$). The time-separation method would therefore overvalue the lottery. For the present-value method, note that the lottery contains three positive outcome streams: $(1200, -600, 1200)$, $(1200, 0, 600)$, $(600, 1200, 0)$. The present value of these streams should be close to each other. The probability that one of these three streams arrives is $2/3$. The present-value method would therefore underweight these positive streams and, thus, undervalue the lottery.

In Lottery 48, at $t = 1$ and at $t = 2$, the outcome 1200 arrives with probability $1/2$. The time-separation method would underweight the positive outcome 1200 in these two periods and therefore undervalue the lottery. For the present-value method, note that the outcome stream $(1200, 1200, 1200)$ arrives with probability $1/6$. The present-value method therefore overweights this stream and, hence, overvalues the lottery.

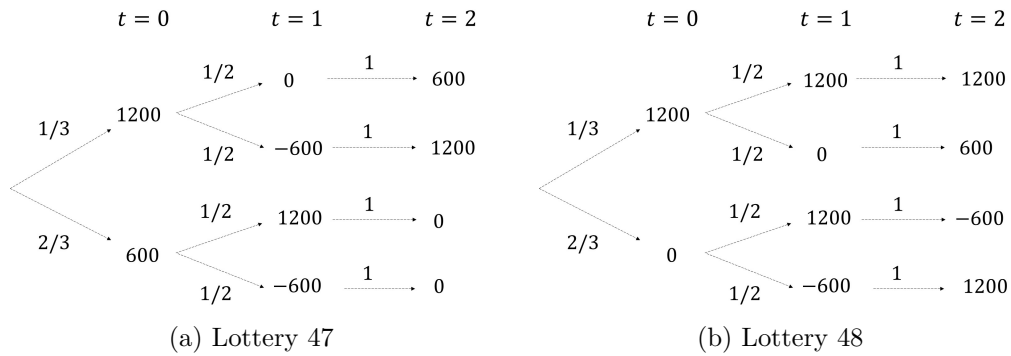


Figure 3.7: Test lottery examples, Lottery Set 6 (high-stake mixed lotteries)

In order to quantify the over- and undervaluation (that was just explained intuitively with the examples), we calculate the certainty equivalent of each lottery using typical atemporal specifications of the weighting and value functions (omitting time discounting). Note that, in line with our experimental design, this certainty equivalent would be received three times. Table 3.2 displays the results for two lotteries as illustration, showing that the degrees of over- and undervaluation are similar. Column (1) shows the certainty equivalent that is calculated with linear probability weighting. Column (2) displays the certainty equivalent that is calculated with the time-separation method, and

Column (3) its relative deviation from the evaluation with linear probability weighting. Column (4) shows the certainty equivalent implied by an evaluation with the present-value method, and Column (5) its relative deviation from the evaluation with linear probability weighting. As shown in Table 3.64 in Appendix 3.9, these characteristics are shared by all 12 test lotteries enabling an a-priori fair comparison of the two application methods.

	No weighting	Time-separation		Present-value	
	CE	CE	Rel. Deviation	CE	Rel. Deviation
	(1)	(2)	(3)	(4)	(5)
Lottery 47	220.3	265.4	+20%	171.8	−22%
Lottery 48	195.9	141.1	−28%	248.8	+27%

Notes: To calculate the certainty equivalents we use the parametric specifications suggested by Tversky and Kahneman (1992) i.e., $v(x) = \mathbb{1}(x \geq 0)x^{0.88} - \mathbb{1}(x < 0)2.25(-x)^{0.88}$, and $w^+(p) = w^-(p) = \frac{p^{0.69}}{(p^{0.69} + (1-p)^{0.69})^{1/0.69}}$ (without time discounting).

Table 3.2: Overview test lotteries

3.3.3 Hypothetical and Incentivized Lotteries

Treatment comparisons are not the main focus of the paper. We implement two treatments in which the remuneration of participants varies. For participants in treatment T1, all decisions are hypothetical and participants receive a fixed payment only (15 euros). For participants in treatment T2 (who also receive the fixed payment of 15 euros), the gain lotteries are incentivized. Each participant in the experiment has a 25% chance to be assigned to the incentivized treatment T2. These two treatments serve as robustness check of whether choices are consistent in both treatments. In the incentivized treatment, the payouts from the three different time periods are also transferred to the participants' bank accounts at three different points in time (the payouts from the first time period are transferred jointly with the payment for participation in the experiment, the other payouts are transferred three and six months later).

For subjects in T2, one gain lottery is randomly selected for payment at the end of the experiment. There is a 99% chance that a low-stake lottery is selected and a 1% chance that a high-stake lottery is selected. Then a standard payment mechanism is employed. A random number is drawn from a uniform distribution, defined over the interval from $y^-/3$ to $y^+/3$, where y^+ is the maximal and y^- the minimal non-discounted sum of payouts of the lottery (these are the limits of the sliders in the decision tasks,

as described in Footnote 5). The terms y^- and y^+ are divided by three, because the certainty equivalent is paid three times. If the drawn random number is greater than or equal to the subject's stated switch point, the subject receives the random number three times. If the random number is lower, the subject keeps the lottery and the reward is determined by a realization of the lottery.

3.3.4 Pre-Analysis Plan

The study was pre-registered at the Open Science Foundation (<https://osf.io/7zyp4>) with a detailed pre-analysis plan (<https://osf.io/fv8a2>). We follow the pre-analysis closely for our main analysis. Minor existing deviations from the pre-analysis plan are explicitly mentioned.

3.3.5 Procedures

The data was collected through CentERpanel on a sample consisting of about 9000 Dutch households that is representative for the Dutch population.⁶ Data collection and data analysis were entirely separated. The experiment was conducted in Dutch. Instructions and other material was translated from English to Dutch by CentERpanel. We made sure in several iterations that the translations are accurate (one of us speaks Dutch and we checked with an experimental economist who is a native speaker). Before starting the decision tasks, subjects had to correctly answer a set of comprehension test questions. The English version of the instructions and comprehension test questions can be found in Appendix 3.9. All subjects who completed the experiment received 15 euros for participating. Subjects in the incentivized treatment received on average 84 euros in addition to this.

In a post-experimental questionnaire, we inquired about the comprehension of the tasks and the attention paid in the experiment:

- During the decision tasks we asked you to position a slider. Was it clear for you what the position of the slider meant?

⁶Two pilots with about 25 subjects each were conducted online with the student subject pool of the Behavioral Lab of the University of St. Gallen. These pilots served to make the elicitation procedure and the instructions as comprehensible as possible.

- During the decision tasks we asked you to evaluate risky options with uncertain payouts at three different points in time. How complicated were these decision tasks?
- Please honestly report your attention during the questionnaire.

Each of these questions only had three answer possibilities. As outlined in our pre-analysis plan, we exclude all subjects from the analysis that answer at least one of these questions with the ‘worst’ answer possibility (indicating that it was unclear what the slider meant, that the decision tasks were too complicated, or that a subject only paid attention in a few parts of the experiment or not at all). In addition (and as pre-registered), we exclude all subjects that completed the tasks with a median decision time of less than 15 seconds. We use such strict exclusion criteria to make sure that we only use data from subjects who understood the tasks and took them seriously (so that the temptation to click through as fast as possible to collect the participation fee in a short period of time does not drive our results).

391 subjects started the decision tasks, 13 of them did not finish the experiment.⁷ Of the remaining 378 subjects, we exclude 192 participants based on the answers to the post-experimental questionnaire and an additional 86 participants that finished the decision tasks with a median time per task of less than 15 seconds. Following our pre-registered data exclusion rules, we therefore drop about 74% of our sample.⁸ Out of the exactly 100 subjects that remain in our main analysis, 27 are in the incentivized treatment and 73 in the hypothetical treatment. Demographic variables in the 100 subjects of the main analysis are similar to the demographic variables among all participants starting the experiment and also among the Center Panel subject pool (details can be found in the appendix, in Table 3.68). Additional information on responses in the post-game survey, the distribution of median decision times, and demographic characteristics of participants and Panel subject pool can be found in Appendix 3.9.

⁷Our pre-registration specifies that the target number of participants was 240. If 240 had been reached by the end of September 2020, the experiment should have stopped, otherwise continued in October. At the end of September, 205 subjects had completed the experiment. We did not receive the data at this point, only summary information on payments and on the responses from the post-experimental questionnaire. Based on this, we asked CentERpanel to continue the data collection in October to obtain in total between 350 and 400 participants. Data collection then stopped at the end of October and we obtained the data from CentERpanel in December.

⁸Using the full sample of 378 subjects would not affect our main conclusion of the superiority of the present-value method over the time-separation method.

Exclusion rates for studies that estimate preference parameters on a representative sample are in general only slightly below ours, despite the fact that most other studies have less complex tasks without time and risk dimensions simultaneously. See, for instance, Booij, Van Praag, and Van De Kuilen (2010), who also use the CenterPanel, with an exclusion rate of 61%, and Dohmen et al. (2005) and Guiso and Paiella (2008), using representative samples in Germany and Italy, who drop 61% and 57% of their observations, respectively (the reasons for exclusion differ between the studies).

3.4 Estimation Procedure

We first introduce the parametric specifications that we consider for the value, weighting, and time-discount functions. Then we discuss the maximum-likelihood procedure with which we estimate the model parameters on the calibration set and how we measure prediction performance on the test set. The described approach is exactly as in the pre-analysis plan.

3.4.1 Parametric Specification

We consider two value functions, three weighting functions and two time-discount functions. These are briefly discussed below and shown in Table 3.3.

As common in the literature (e.g., Sugden, 2003; Köbberling and Wakker, 2005; and Abdellaoui and Kemel, 2013), we assume that the value function is composed of a loss aversion coefficient λ and basic utility functions for gains and losses. We focus on the two most common specifications, power utility (forcing the power coefficients of gains and losses to be identical, as is common to obtain an interpretable loss aversion coefficient; e.g., Köbberling and Wakker, 2005; Harrison and Rutström, 2008; Post et al., 2008; and Tanaka, Camerer, and Nguyen, 2010) and exponential utility.

We focus on three common parametric specifications of the probability weighting functions. The same type of function is always used for gains and for losses, but we allow the parameters to differ. The first option we consider is the function used by Tversky and Kahneman (1992), with only one parameter. The second weighting function considered in this study is the two-parameter specification proposed by Prelec et al. (1998). The third weighting function considered in this study is the two-parameter specification proposed

Specification	Parameters
Value functions	
Power utility: $v(x) = \mathbb{1}_{x \geq 0} x^\alpha - \mathbb{1}_{x < 0} \lambda (-x)^\alpha$	α, λ
Exponential utility: $v(x) = \mathbb{1}_{x \geq 0} \frac{1 - \exp(-\alpha x)}{\alpha} - \mathbb{1}_{x < 0} \lambda \frac{1 - \exp(\beta x)}{\beta}$	α, β, λ
Probability weighting functions (gains and losses)	
Tversky and Kahneman (1992): $w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}$	γ^+, γ^-
Prelec (1998): $w(p) = \exp(-\eta(-\ln(p))^\gamma)$	$\eta^+, \eta^-, \gamma^+, \gamma^-$
Goldstein Einhorn (1987): $w(p) = \frac{\eta p^\gamma}{\eta p^\gamma + (1-p)^\gamma}$	$\eta^+, \eta^-, \gamma^+, \gamma^-$
Time-discount functions	
Exponential discounting: $\delta(t) = \exp(-rt)$	r
Quasi-Hyperbolic discounting: $\delta(t) = \mathbb{1}_{t=0} + \mathbb{1}_{t>0} k \exp(-rt)$	k, r

Notes: This table shows the formulas for the considered value functions, probability weighting functions (for gains and losses), and time-discount functions. For each function the table lists the parameters that have to be estimated.

Table 3.3: Function specifications

by Goldstein and Einhorn (1987).

The time-discount function captures the discounting of future outcomes. We focus on the two most common specifications, exponential discounting and quasi-hyperbolic discounting (which discounts all future outcomes when compared to rewards at time $t = 0$, in addition to exponential discounting).

As displayed in Table 3.4, we analyze each possible combination of these functions (there are 12 such combinations) for the time-separation method as well as for the present-value method.

3.4.2 Maximum-Likelihood Estimation

Each participant reports a multi-period certainty equivalent for a total of 48 lotteries, consisting of 36 calibration and 12 test lotteries. We use the multi-period certainty equivalents reported for the calibration lotteries to estimate the model parameters.

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Value	Power	x	x	x	x	x	x						
	Exponential							x	x	x	x	x	x
Weighting	T+K (1992)	x	x					x	x				
	Prelec (1998)			x	x					x	x		
	G+E (1987)					x	x					x	x
Discount	Exponential	x		x		x		x		x		x	
	Quasi hyp.		x		x		x		x		x		x

Notes: This table shows the twelve combinations of the two types of value functions, three types of probability weighting functions, and two types of time-discount functions.

Table 3.4: Overview function combinations

Consider model Combination C1 with parameters $\alpha, \lambda, \gamma^+, \gamma^-$ and r , where the parameters have the meanings as above. That is, the model corresponds to power utility, a Tversky-Kahnemann probability weighting function, and exponential discounting (the other model specifications are handled accordingly). As discussed before, we allow the parameters of the weighting function to differ for gains and losses. These parameters are labeled as γ^+ and γ^- .

Denote by $V(L_j|\alpha, \lambda, \gamma^+, \gamma^-, r)$ the PT value of the j -th lottery (L_j), arising with one given parametric specification. The multi-period certainty equivalent of the lottery, ce_j , is a certain payout that arises three times (at $t = 0$, at $t = 1$, and at $t = 2$), so that the three payments jointly have a PT value equal to the PT value of the lottery. The PT value of the certainty equivalent is $v(ce_j) + \exp(-r)v(ce_j) + \exp(-2r)v(ce_j)$, independently of which application method of prospect theory is used (the payment is certain, there is thus no probability weighting). Indifference between the certainty equivalent and the lottery implies that the certainty equivalent of a lottery can be calculated as $ce_j(\alpha, \lambda, \gamma^+, \gamma^-, r) = v^{-1}\left(\frac{1}{1+\exp(-r)+\exp(-2r)}V(L_j|\alpha, \lambda, \gamma^+, \gamma^-, r)\right)$, with v^{-1} denoting the inverse of the value function.

Following existing literature (e.g., Hey, Morone, and Schmidt, 2009; Bruhin, Fehr-Duda, and Epper, 2010), we write the observed certainty equivalent of participant i , $CE_{i,j}$, as $CE_{i,j} = ce_j + \epsilon_{i,j}$ (note that we use capital letters for observed data). The term $\epsilon_{i,j}$ reflects a variety of sources (among others hurrying or inattentiveness). We assume that $\epsilon_{i,j}$ is normally distributed with mean 0 and standard deviation $\sigma_{i,j}$. In addition, we allow for two sources of heteroskedasticity. First, as the employed set of lotteries has different payout ranges, we assume that the error variance is proportional to the payout range of

the lottery. The payout range of lottery j , w_j , is calculated as $w_j = |L_{j,max} - L_{j,min}|$, where $L_{j,max}$ denotes the maximal and $L_{j,min}$ the minimal non-discounted sum of payouts of lottery j . Second, as participants may be heterogeneous (e.g., with respect to their attention span), we allow the error variance to differ by participant. This yields the form $\sigma_{i,j} = \epsilon_i w_j$ for the standard deviation of the error term, where ϵ_i denotes a participant-specific parameter.

Given our assumptions on the distribution of the error term, the contribution of participant i to the likelihood function L can be expressed as

$$f(\theta, \epsilon_i | CE_i) = \prod_{j=1}^{36} \frac{1}{\sigma_{i,j}} \phi \left(\frac{CE_{i,j} - ce_j(\theta)}{\sigma_{i,j}} \right),$$

where the vector $CE_i = (CE_{i,1}, \dots, CE_{i,36})$ contains the certainty equivalents participant i reports for the 36 calibration lotteries, and the vector $\theta = (\alpha, \lambda, \gamma^+, \gamma^-, r)$ contains the parameters of the model. Furthermore, ϕ denotes the density of the standard normal distribution. Using data from all n participants, the log-likelihood function is given by

$$\ell(\theta, \epsilon | CE) = \log L(\theta, \epsilon | CE) = \sum_{i=1}^n \log f(\theta, \epsilon_i | CE_i) = \sum_{i=1}^n \sum_{j=1}^{36} \log \left[\frac{1}{\sigma_{i,j}} \phi \left(\frac{CE_{i,j} - ce_j(\theta)}{\sigma_{i,j}} \right) \right],$$

where the vector $CE = (CE_1, \dots, CE_n) = (CE_{1,1}, \dots, CE_{1,36}, \dots, CE_{n,1}, \dots, CE_{n,36})$ contains the certainty equivalents reported for the calibration lotteries by all n participants, and the vector $\epsilon = (\epsilon_1, \dots, \epsilon_n)$ contains the participant-specific error variance parameters.

For the estimation of the parameters, we maximize the log-likelihood function using standard iterative algorithms. With this estimation strategy we simultaneously estimate the model parameters $(\alpha, \lambda, \gamma^+, \gamma^-, r)$ and the participant-specific error variance parameters $\epsilon_1, \dots, \epsilon_n$.

3.4.3 Measurement of Prediction Performance on the Test Set (Main Outcome Variable)

We use the multi-period certainty equivalents reported for the 12 test lotteries to measure the (out-of-sample) performance of the two methods. For each of the two methods we use the model parameters that were estimated on the calibration set (e.g., $\hat{\alpha}, \hat{\lambda}, \hat{\gamma}^+, \hat{\gamma}^-$,

$\hat{r}$) to predict choices of the multi-period certainty equivalents in the test set,

$$\widehat{ce}_j = v^{-1} \left(\frac{1}{1 + \exp(-\hat{r}) + \exp(-2\hat{r})} V(L_j | \hat{\alpha}, \hat{\lambda}, \hat{\gamma}^+, \hat{\gamma}^-, \hat{r}) \right).$$

As measure of prediction performance, we use the (weighted) mean squared errors. The (weighted) mean squared error of participant i is calculated as

$$MSE_i = \frac{1}{12} \sum_{j=1}^{12} \left(\frac{1}{w_j} (CE_{i,j} - \widehat{ce}_j) \right)^2,$$

where $w_j = |L_{j,max} - L_{j,min}|$, as before. The weighting ensures that the error is not disproportionately driven by lottery choices involving large (absolute) payout amounts. Using data from all n participants, we define our main outcome variable as

$$MSE = \frac{1}{n} \sum_{i=1}^n MSE_i.$$

Out of all 24 combinations of application method and functional specification, we consider the combination best that leads to the lowest MSE .

The predicted certainty equivalents $\widehat{ce}_j$ and thus MSE_i and MSE depend on the choice of the application method. We denote by MSE_{TS} and MSE_{PV} the MSE resulting from the evaluation under the time-separation method and under the present-value method, respectively (given a combination of value, probability-weighting, and time-discount functions). We denote the difference between these two values by

$$\Delta MSE := MSE_{TS} - MSE_{PV}.$$

For each of the 12 functional specifications, ΔMSE indicates whether one application method describes decisions better than the other.

3.4.4 Tests and Standard Errors

To test whether the two application methods differ with respect to their prediction performance, we investigate the 12 functional specifications in isolation. For each specification we test whether the difference between the two (weighted) mean squared errors, i.e. ΔMSE , is statistically significant different from 0. The null hypothesis H_0 is $\Delta MSE = 0$

and the (two-sided) alternative hypothesis H_a is $\Delta MSE \neq 0$.

Therefore, we conduct (non-parametric) paired bootstrap tests. We draw from our sample with replacement to obtain bootstrap samples of the same size as our original sample (resampling is done at the level of participants). For each bootstrap sample we follow the procedure described in Sections 3.4.2 and 3.4.3. We first estimate the parameters on the calibration lotteries and then calculate the two (weighted) mean squared errors (one for each application method) on the test lotteries. We denote by $MSE_{b,TS}$ and $MSE_{b,PV}$ the two MSE s that are estimated on bootstrap sample b and by ΔMSE_b their difference, $\Delta MSE_b = MSE_{b,TS} - MSE_{b,PV}$. We reject the null hypothesis if $\Delta MSE_b \geq 0$ in less than 2.5% of the bootstrap samples or if $\Delta MSE_b \leq 0$ in less than 2.5% of the bootstrap samples.

We also use these bootstrapped samples to provide standard errors of the parameter estimates (estimated on the calibration lotteries of the full sample).

3.4.5 Final Re-estimation

In a final step, we pool the data on the calibration and test lotteries (thus making use of the full 48 certainty equivalents per participant) to reestimate the parameters, at least for the most successful combination of application method and functional specification (to provide a complete model benchmark of how to best apply intertemporal prospect theory). We again provide bootstrapped standard errors of parameters (as for the parameters estimated on the calibration set).

3.5 Results

We first focus on the main result, which is the comparison of the prediction performance of the two application methods. Thereafter, we re-estimate the parameters on the pooled training and test set. Analyses that are pre-registered as additional analyses can be found thereafter in Sections 3.5.3 and 3.5.4. As specified in the pre-analysis plan, we analyze the data from both treatments jointly, as they are sufficiently similar according to the pre-defined criteria (more detail on this can be found in Section 3.5.5 below). The number of observations for the analyses is 100.

3.5.1 Time-separation vs. Present-value Method

As discussed in Section 3.4, we first estimate the parameters for each of the 12 combinations separately on the calibration lotteries. We then use these parameters to compare the prediction performance of the models for the test lotteries. The parameter estimates on the calibration set (which are identical for both application methods) are not very different from the estimates on the whole sample (shown below in Section 3.5.2), therefore we do not discuss them here (they can be found in Appendix 3.9). Note that the probability-weighting functions are clearly non-linear in all cases, which is necessary for the application methods to lead to different predictions on the test set.

The main result of the comparison of the different application methods can be found in Figure 3.8. This figure shows the mean squared errors on the test set for both application methods and all 12 combinations of function specifications. It can be seen that the present-value method always performs better than the time-separation method. This difference is sizable and highly statistically significant: Figure 3.9 shows the difference between the mean squared errors jointly with bootstrapped 95%-confidence intervals.⁹

The difference in prediction performance is not driven by a particular subset of the test lotteries. For each of the twelve combinations, the present-value method has a lower MSE than the time-separation method for each single test lottery (Table 3.70 in the appendix contains the MSE per lottery for each function combination). To illustrate the magnitude of the differences in prediction performance, Table 3.5 shows a lottery-by-lottery comparison for all test lotteries for combination C1, with the mean absolute prediction errors instead of mean squared errors for easier interpretation (Table 3.69 in the appendix shows a by-lottery comparison of all twelve combinations).

One can also illustrate the difference by classifying participants as time-separation or present-value types (for illustration; this classification is not mentioned in the pre-analysis plan). If the MSE of one participant for one method is greater than the MSE for the other with a difference of at least one standard error (of the MSE difference between the two methods), a participant is classified as a time-separation or a present-value type (otherwise the person remains unclassified). Table 3.6 displays the results. For all twelve

⁹The pre-registration states that we also provide a test in which we compare the best performing of the 12 combinations for the present-value method with the best performing combination for the time-separation method. This difference is naturally also significant, because the performance of the function combinations C1-C12 within one application method is very similar (which can be seen from Figures 3.8 and 3.9).

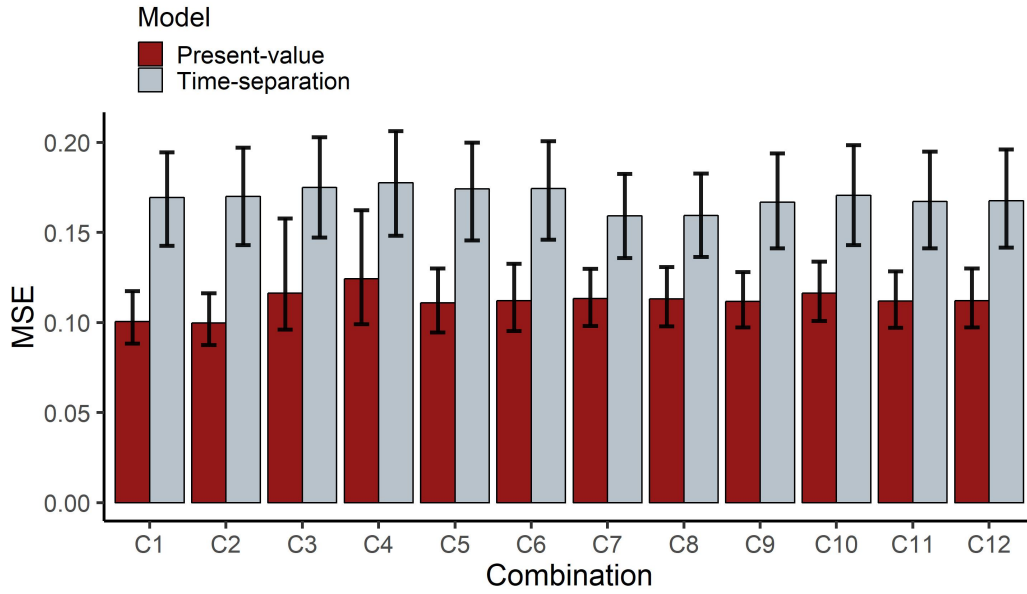


Figure 3.8: MSE for both application methods (all function combinations)

Notes: This figure shows mean squared errors of present-value and time-separation method on the test set for all 12 function combinations (with bootstrapped 95% confidence intervals).

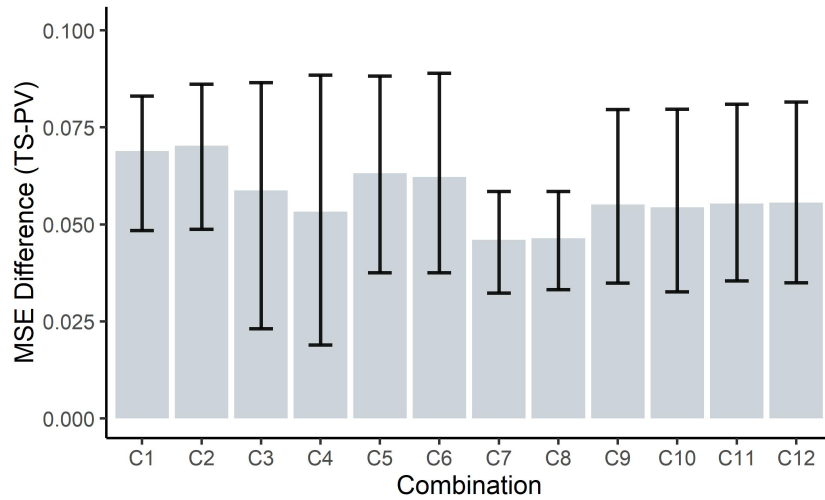


Figure 3.9: Difference in MSE between the application methods (all function combinations)

Notes: This figure shows the average differences in mean squared errors (MSE of time-separation method minus MSE of present-value method) with bootstrapped 95% confidence intervals.

	Low-stake lotteries							High-stake lotteries				
	L7	L8	L15	L16	L23	L24	L31	L32	L39	L40	L47	L48
Payout range	23	20	23	20	30	50	467	400	467	400	600	1000
Mean error TS	6	8.1	7.3	5.6	7.9	16.7	144.1	148.6	146	124.9	180	319.9
Mean error PV	5.2	5.6	6.1	5.6	7.2	14.6	108.5	118	114.4	115	150.7	276.8

Notes: The mean absolute prediction error of Lottery j is calculated as $\text{mean}(|CE_{i,j} - \widehat{ce}_j|)$, with $CE_{i,j}$ denoting the certainty equivalent subject j reported for lottery j and $\widehat{ce}_j$ denoting the predicted certainty equivalent resulting from the parameters estimated on the calibration set.

Table 3.5: Mean absolute prediction error (by lottery)

combinations, the vast majority of subjects is classified as present-value type. The share of present-value types ranges from 81 to 89 percent, with 8 to 18 percent unclassified and 1 to 10 percent time-separation types. Figure 3.21 in the Appendix, displays the distribution of the difference between the two MSEs showing that these are sizable for a majority of the participants.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Time-separation types	10	5	1	1	1	1	5	5	3	1	2	1
Present-value types	81	84	83	81	89	88	87	87	86	89	88	88
Unclassified	9	11	16	18	10	11	8	8	11	10	10	11

Notes: Participant i is classified as time-separation type if $MSE_i^{PV} - SE(\Delta MSE) > MSE_i^{TS}$ or as present-value type if $MSE_i^{TS} - SE(\Delta MSE) > MSE_i^{PV}$. $SE(\Delta MSE)$ denotes the standard error of the difference in MSE between the two methods.

Table 3.6: Participant types

3.5.2 Parameter Estimates

Here, we present and discuss the parameter estimates from the reestimation on the full set of lotteries. Because the present-value method is the superior evaluation method, we only present the parameter estimates resulting from an evaluation under this method. The results for the time-separation method can be found in Appendix 3.9.

Which utility function is used (power or exponential) and which of the two-parameter probability-weighting functions is used (Prelec et al. (1998) or Goldstein and Einhorn (1987)) has only minor implications for the shapes of the calibrated functions. We therefore only show the parametrizations of the four combinations that employ a power utility and either one-parameter weighting functions as suggested by Tversky and Kahneman (1992) (C1 and C2) or two-parameter weighting functions suggested by Goldstein and

Einhorn (1987) (C5 and C6). C1 and C5 use exponential time-discounting, C2 and C6 quasi-hyperbolic discounting. The estimates are shown in Table 3.7 (with standard errors in parentheses). The estimates for all twelve model combinations can be found in Appendix 3.9.

Combination	Value			Weighting			Discounting	
	α	β	λ	$\gamma+$	$\gamma-$	$\nu+$	$\nu-$	r k
C1	1.195 (0.068)		1.069 (0.096)	0.535 (0.045)	0.551 (0.06)			0.117 (0.036)
C2	1.172 (0.061)		1.065 (0.121)	0.547 (0.043)	0.565 (0.057)			0.016 (0.025) 0.863 (0.043)
C5	1.091 (0.035)		1.037 (0.127)	0.426 (0.066)	0.448 (0.073)	0.766 (0.074)	0.786 (0.071)	0.070 (0.028)
C6	1.085 (0.03)		1.101 (0.163)	0.423 (0.07)	0.451 (0.073)	0.786 (0.073)	0.796 (0.068)	0.0012 (0.016) 0.884 (0.045)

Notes: This table shows the parameter estimates on the full set of lotteries (calibration plus test set) for the present-value method, for four selected function combinations. Estimates for all twelve function combinations and for the time-separation method can be found in Appendix 3.9.

Table 3.7: Overview parameter estimates on full sample (48 lotteries)

Value function: The value functions consist of a basic utility functions for gains and losses and a loss aversion parameter (λ). The basic utility functions are in general close to linear, with utility in the gain domain mostly slightly convex and in the loss domain slightly concave (for the four combinations C9 to C12 that employ an exponential utility and two-parameter probability weighting functions, the estimated utility is slightly concave for gains and convex for losses, see the full Table 3.72). In the atemporal literature the utility for gains is generally found to be concave and the utility for losses is found to be convex or linear.¹⁰ A potential explanation for this relates to complexity. The present-value method aggregates the outcomes of each stream into a single present value. A simple form of aggregation is the (time-discounted) sum of all outcomes (monetary values). When subjects aggregate outcomes, they may, due to the complexity of the task, evaluate outcomes in payout terms rather than in (non-linear) utility terms. Note that Abdellaoui et al. (2013), who estimate intertemporal utility without risk, similarly find that utility is mildly convex for gains and mildly concave for losses.

The second component of the value function is the loss aversion parameter λ . The

¹⁰However, similar shapes have already been observed in the atemporal literature. Bruhin, Fehr-Duda, and Epper (2010), for instance, calibrate a combination of Goldstein-Einhorn weighting functions and power utility, as our C5 and C6, with very similar estimates of weighting and utility functions, including basic utility that is convex for gains and concave for losses.

loss aversion parameters are on average slightly above one. This is lower than what is usually observed in the atemporal literature. According to a recent meta study (Brown et al., 2021), the median loss aversion parameter among 286 aggregate level studies is 1.5. However, the few studies that estimate loss aversion in an intertemporal context (without risk) also find loss aversion coefficients closer to one (Abdellaoui, l’Haridon, and Paraschiv, 2013; Abdellaoui et al., 2013). Following the complexity explanation from above, subjects may evaluate outcomes in monetary values for simplicity rather than in utility terms and thereby not distinguish between losses and gains (as these do not appear in pure monetary values). A second potential explanation is that participants may aggregate losses and gains rather than evaluating these in isolation. Suppose, for instance, that an outcome stream yields 60 at $t = 1$ and -40 at $t = 2$. If subjects aggregate gains and losses, the evaluation of the stream should (neglecting time discounting) be close to the evaluation of a payout of 20 at $t = 1$ and no payout at $t = 2$. The present-value method (as also the time-separation method), however, transforms each outcome to a utility term before aggregating. The evaluation in isolation is only consistent to the aggregation of gains and losses if the loss aversion parameter is close to 1. A version of the present-value method (pre-registered as additional analysis) calculating present values in monetary terms before entering them in a utility function is treated below in Section 3.5.4.

Probability weighting functions: The calibrations of the probability-weighting functions turn out to be very similar for gains and for losses for all function combinations, suggesting that one can use the same functions in the gain and in the loss domain (reducing the number of model parameters). For all specifications, an inverse S-shape is found, as common in the atemporal literature. The shapes of the weighting functions are also similar across the different specifications, with the two-parameter weighting functions ascending faster for low values than the one-parametric Tversky-Kahneman specification. Figure 3.10 displays the estimated weighting functions for gains for model combinations C1 and C5 as illustrations. In general, our estimates of probability weighting functions are very similar to those estimated in atemporal contexts (e.g., Stott, 2006; Booij, Van Praag, and Van De Kuilen, 2010; Bruhin, Fehr-Duda, and Epper, 2010).

Time-discount function: Exponential discounting and quasi-hyperbolic discounting lead to very similar prediction performances in our setting. The estimates for exponen-

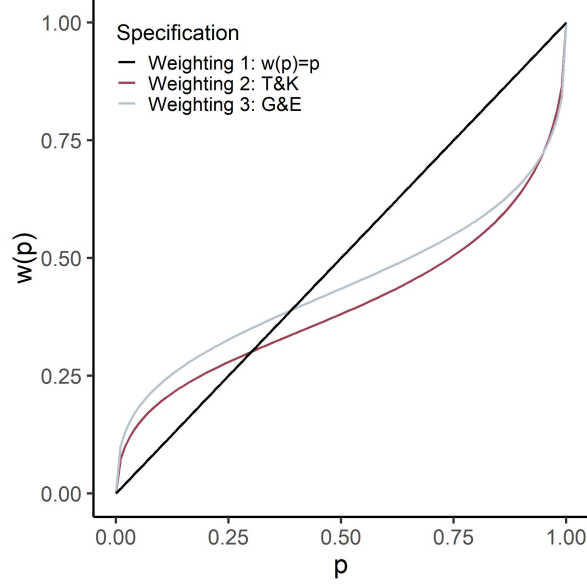


Figure 3.10: Estimated probability-weighting functions

Notes: This figure shows the estimated weighting functions for gains for function combinations C1 and C5 (for the present-value method). C1 and C5 both use a power value function and exponential discounting.

tial discounting reach from zero to about 12% per quarter. Estimates for quasi-hyperbolic discounting reach from no discounting at all to discounting all future payments by about 15% (with very small additional exponential discounting when all future outcomes are already discounted). These discounting patterns are similar to those found in risk-less intertemporal decision tasks, as reported in the recent meta study by Havránek, Irsova, and Matousek (2021).

3.5.3 The Importance of the Components of PT in Intertemporal Settings

As mentioned in the pre-analysis plan, we also investigate the importance of PT's components. To do so, we show how the performance deteriorates when the probability weighting functions are linear, when there is no loss aversion, or when the utility functions are linear (with all free parameters estimated anew). We also compare the methods to discounted expected utility maximization. In this section we focus on the results for the present-value method, an investigation for the time-separation method can be found in Appendix 3.9.

The analyses in Sections 3.5.3 and 3.5.4 are described as additional analyses in the

pre-analysis plan (with little detail; the analysis is kept as similar to the main analysis as possible). The core design feature of our calibration set is that the calibrations are the same for time-separation and present-value method. In addition, the test lotteries are such that the two methods over- or underestimate the lotteries to a similar extent with typical atemporal calibrations. These features ensure that our design does not favor one of the two methods. Both features, however, do not hold when also considering other methods (including expected discounted utility). Therefore, the comparison here differs as follows.

We randomly select six of the eight lotteries from each set, implying a total of 36 lotteries, as the new calibration lotteries. We repeat this random selection process 10 times. For each of these ten repetitions the 36 calibration lotteries are used to calibrate a models' parameters. The other twelve lotteries (two per set) are used as test lotteries to compare the predictive performance, measured by the (weighted) MSE. The numbers of calibration and test lotteries are therefore the same as in the main analysis. We denote by MSE_{S_i} the (weighted) MSE of the random selection S_i , $i \leq 10$. The main outcome variable is the mean of these ten values,

$$MSE = \frac{1}{10} \sum_{i=1}^{10} MSE_{S_i}$$

Bootstrapped confidence intervals for the MSE are obtained as in the main analyses.

The results are shown in Figure 3.11. The prediction performances of models with linear utility for gains and losses ('PT: Linear Utility'; this model allows for a loss aversion coefficient different from one) or no loss aversion ('PT: No Loss Aversion') are almost identical to the performance of the full PT application ('PT: All Components'). The same holds if utility is not only required to be linear for gains and losses, but on the whole domain, including the absence of loss aversion ('PT: Linear Utility and No Loss Aversion'). This implies that utility curvature and loss aversion can be omitted if a more parsimonious model is desired. However, forcing linear-probability weighting ('PT: Linear Probability Weighting') predicts decisions significantly worse.¹¹ These findings

¹¹Several of the MSE bars in Figure 3.11 are identical across the function combinations. For instance, when utility is assumed to be linear there is no more distinction between power utility (C1 to C6) and exponential utility (C7 to C12). For EDU, there are even only two specifications: one with power utility (C1 to C6) and one with exponential utility (C7 to C12), as there is neither probability weighting nor hyperbolic discounting.

are consistent with the parametrizations discussed in Section 3.5.2, which exhibit almost linear utility with a loss aversion parameter close to one and highly non-linear probability weighting functions.

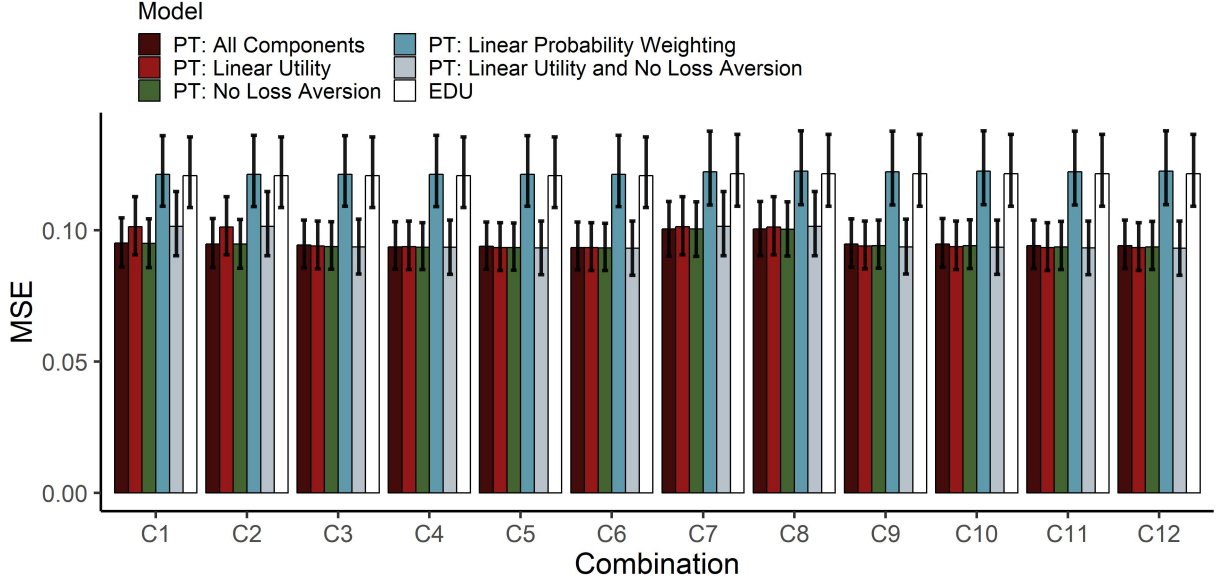


Figure 3.11: MSE, PT components (all function combinations)

Notes: This figure compares the prediction performance of the present-value method to versions of it with some components absent and to expected utility theory (parameters are estimated anew for each method). The versions are (from left to right for each of the 12 function combinations) the present-value method with all components ('PT: All Components'), with linear utility for gains and losses still including a loss-aversion parameter ('PT: Linear Utility'), with a loss-aversion parameter of 1 ('PT: No Loss Aversion'), with linear-probability weighting ('PT: Linear Probability Weighting'), with linear utility for gains and losses and a loss-aversion parameter of 1 ('PT: Linear Utility and No Loss Aversion'); on the right expected discounted utility is shown ('EDU').

We also compare the prediction performance of PT models to standard expected discounted utility models with linear probability weighting, no loss aversion, and no hyperbolic discounting ('EDU'). Figure 3.11 shows that EDU predicts decisions significantly worse than PT, including the sparser versions that still allow for non-linear probability weighting. The prediction performance of EDU and the PT version with linear probability weighting is, however, almost identical. The calibration of EDU utility functions is almost linear.

3.5.4 A Third Way of Applying Prospect Theory in Intertemporal Situations

In addition to the two main methods, we also analyze the performance of a third application method of prospect theory (as described in the pre-analysis plan). This method is in spirit similar to the present-value method. Whereas the regular present-value method calculates the present value of an outcome stream (before probability weighting plays a role) as $PV(o_j) = \sum_{t=0}^{T-1} \delta(t)v(o_{j,t})$, the third application method calculates it as $PV(o_j) = v\left(\sum_{t=0}^{T-1} \delta(t)o_{j,t}\right)$. That is, instead of calculating the present value in utility terms by discounting the utility obtained each period, it first calculates a present value in monetary terms and then transforms this into utility (this happens again before probability weighting plays a role). We call the third application method monetary present-value method.¹²

We find the method intuitively appealing, because the outcomes of the lotteries are of monetary nature and money can be transferred from one period to another (in contrast, we find the regular present-value more intuitive if the outcomes are not of monetary nature but, for example, final consumption that cannot be transferred from one period to another). One may also argue that aggregating outcomes in monetary terms is less demanding than aggregating outcomes in utility terms, so that the method may correspond more closely to simple decision making by participants.

Figure 3.12 shows the predictive power of the monetary present-value method and the regular present-value method. The comparison is again based on 10 random draws of calibration and test lotteries, as in Section 3.5.3 (the degrees of freedom are always identical for a given function combination). It can be seen that the predictive power of the two present-value methods is virtually identical.

We re-calibrate the functions for the monetary present-value method on the full set of lotteries. As the choice of the utility function (power or exponential) and also the choice of the two-parameter probability weighting function (Prelec et al., 1998, or Goldstein and Einhorn, 1987) has again only minor implications for the parametrizations, we only show combinations C1, C2, C5, and C6 in Table 3.8, as before (for estimates of all combinations,

¹²We are not aware that this method has, in this form, been explicitly mentioned in the literature. Note, however, that the “time-first” specification in Rohde and Yu (2022), which is kept general, can be restricted to become the regular or the monetary present-value method.

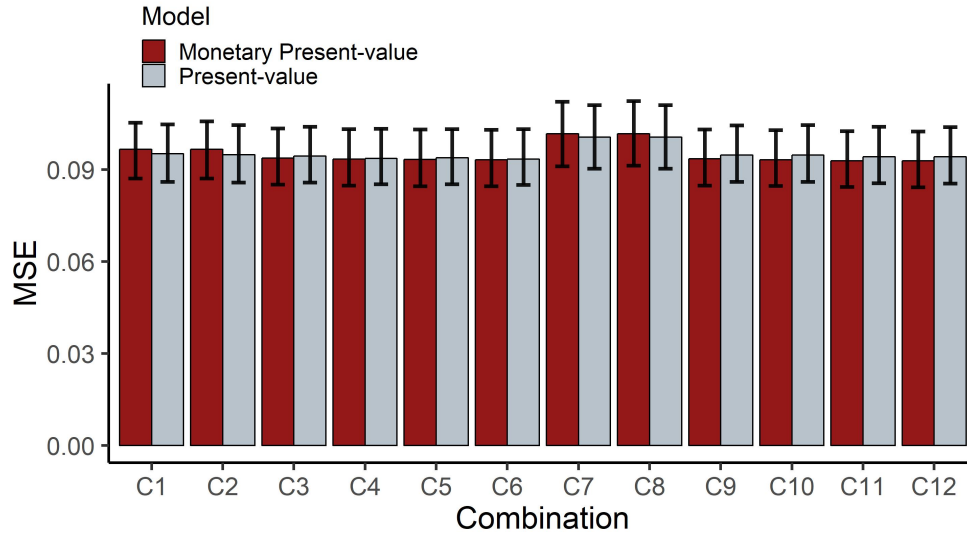


Figure 3.12: MSE for the present-value method and the monetary present-value method

Notes: This figure shows mean squared errors of the monetary present-value and the (regular) present-value method on the test set for all 12 function combinations (with bootstrapped 95% confidence intervals).

see Appendix 3.9).

Combination	Value			Weighting			Discounting	
	α	β	λ	$\gamma+$	$\gamma-$	$\nu+$	$\nu-$	r k
C1	1.179 (0.075)	1.133 (0.227)	0.579 (0.04)	0.592 (0.058)				0 (0)
C2	1.182 (0.072)	1.141 (0.224)	0.576 (0.041)	0.576 (0.058)				0 (0)
C5	0.915 (0.049)	1.033 (0.223)	0.403 (0.068)	0.406 (0.075)	1.036 (0.097)	1.05 (0.112)	0.041 (0.023)	1 (0.001)
C6	0.915 (0.049)	1.087 (0.200)	0.406 (0.069)	0.421 (0.074)	1.03 (0.096)	1.05 (0.118)	0.001 (0.009)	0.938 (0.032)

Notes: This table shows the parameter estimates on the full set of lotteries (calibration plus test set) for the monetary present-value method, for four selected function combinations. Estimates for all twelve function combinations can be found in Appendix 3.9.

Table 3.8: Calibration monetary present-value method

The calibrations are overall similar to those of the regular present-value method (Table 3.7). There are some differences, however. The loss-aversion coefficient is on average slightly higher for the monetary present-value method. This makes intuitively sense if one considers loss aversion to be present at the “overall” level rather than in each period: the loss-aversion coefficient in the monetary present-value method captures aversion to losses when the payouts over the periods are summed up (after discounting), while the

loss-aversion coefficient in the regular present-value method captures aversion to losses within each period. While the utility is still mildly convex for gains and mildly concave for losses for the combinations that employ the one-parameter weighting function the utility is now mildly concave for gains and mildly convex for losses for combinations that employ a two-parameter weighting function.

For all combinations, the curvature parameters of the probability weighting functions (γ^+ and γ^-) are almost identical to those estimated for the regular present-value method. All functions, thus, again have an inverse-s shape. However, for the two-parametric probability weighting functions, the elevation (measured by ν^+ and ν^-) is greater, implying more optimism for gains and more pessimism for losses, when compared to the estimates for the regular present-value method. Figure 3.13 shows an example of the different weighting functions (estimated weighting function for gains for combination C5).

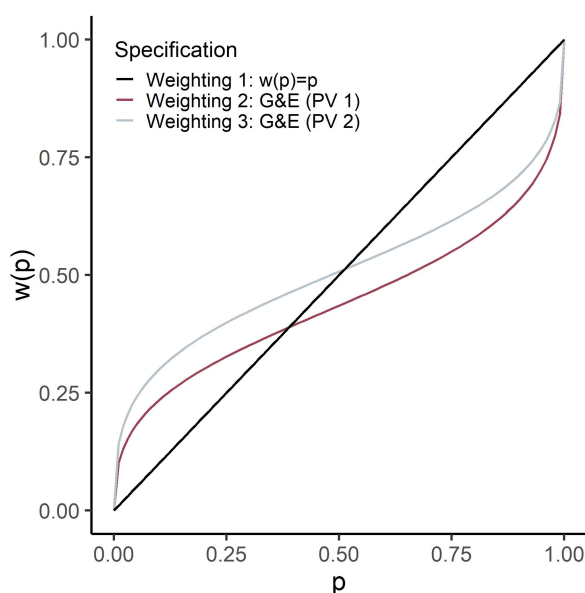


Figure 3.13: Probability-weighting function for gains for the regular (PV 1) and the monetary (PV 2) present-value methods

Notes: This figure shows estimated Goldstein-Einhorn probability weighting functions for gains for the present-value method (PV1) and the monetary present-value method (PV2) for function combination C5 (this function combination uses a power value function and exponential discounting).

Estimates of time discounting are somewhat lower for the monetary present-value method than for the regular one. For exponential discounting, estimated discounting per quarter reaches from zero to about 7%. For quasi-hyperbolic discounting, all future outcomes are estimated to be discounted by zero to about 12% (with very little additional

exponential discounting).

We repeat the analysis of Section 3.5.3 for the monetary present value method to find out which components of PT are most important for the prediction performance. As for the regular present-value method, probability weighting is by far most important. Relying on linear utility for gains and losses (with or without loss aversion) makes no noticeable difference for prediction performance. The results can be found in Figure 3.23 in the appendix.

3.5.5 Treatment Comparison

To test whether decisions differ between the two treatments, we proceed as specified in our pre-analysis plan. For each of the 16 gain lotteries, we test with exact tests for comparing means (Schlag, 2008) whether the means of the stated certainty equivalents between the two treatments differ. To counteract the problem of multiple testing, we correct the p -values using the Bonferroni-Holm method (as described in the pre-analysis plan). None of these tests are significant (using t-tests or Wilcoxon-Mann-Whitney tests instead also yields no significant differences; even without corrections for multiple testing none of the p -values for any single lottery are below 0.05.). Details on these test results can be found in Appendix 3.9. Figure 3.14 contains boxplots of choices for all gain lotteries, showing that choices are very similar in both treatments.

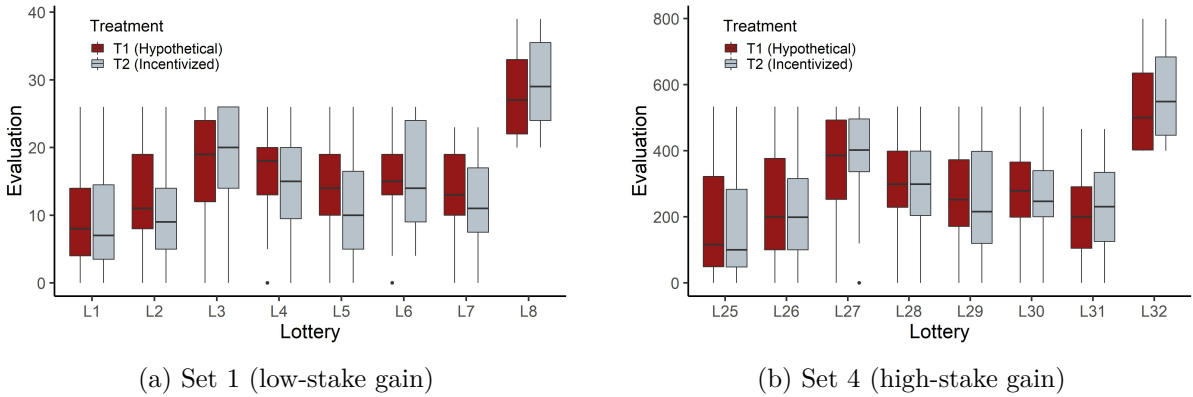


Figure 3.14: Evaluations (stated certainty equivalents) in T1 and T2

Notes: This figure shows boxplots of reported certainty equivalents for all gain lotteries, split up according to whether the decisions are hypothetical or with monetary incentives.

These results confirm earlier findings in the literature. In the elicitation of risk and time preferences (situations in which lies by participants would neither increase their mon-

etary rewards nor their social image or self image; these situations are naturally different from game-theoretic settings), it is predominantly found that there are no considerable differences between hypothetical and incentivized choices (e.g., Abdellaoui, l’Haridon, and Paraschiv, 2011; Brañas Garza et al., 2020; Hackethal et al., 2020).

3.6 Conclusion

Our pre-registered experiment on a representative sample of the Dutch population tests the performance of applications of prospect theory in intertemporal settings. We find that the present-value method (aggregating first over time) performs much better than the time-separation method (aggregating first over risk). The method also performs much better than expected discounted utility theory.

While the choice of present-value method or time-separation method has a sizable impact on the explanatory power, the functional form of value, probability-weighting, and time-discounting functions has only a negligible effect on the explanatory power. We provide parameter estimations for twelve combinations of functional forms. There may be theoretical considerations for preferring some combinations over others. If one is only interested in the predictive power (possibly favoring a combination with few parameters), we recommend using the following specifications of a power utility and Tversky-Kahneman probability-weighting functions for gains and losses, combined with an exponential discounting of 12% per quarter: $v(x) = \mathbb{1}(x \geq 0)x^{1.20} - \mathbb{1}(x < 0)1.07(-x)^{1.20}$, and $w^+(p) = w^-(p) = \frac{p^{0.54}}{(p^{0.54} + (1-p)^{0.54})^{1/0.54}}$ (labeled combination C1 in Table 3.4 above).¹³ As alternative, if one prefers to use a two-parametric probability-weighting function to allow for more flexibility (for theoretical arguments in favor of a two-parametric function, see Fehr-Duda and Epper, 2012), we recommend using the following specifications of a power utility and Goldstein-Einhorn weighting functions, combined with exponential discounting of 7% per quarter: $v(x) = \mathbb{1}(x \geq 0)x^{1.09} - \mathbb{1}(x < 0)1.04(-x)^{1.09}$, and $w^+(p) = w^-(p) = \frac{0.78p^{0.44}}{0.78p^{0.44} + (1-p)^{0.44}}$ (C5). This specification has a prediction performance that is almost as good as the specification mentioned earlier and the parameter values

¹³This is the combination with with the best out-of-sample explanatory power. It is also the combination with the lowest number of parameters. The calibration stems from the whole set of lotteries – in the exact calibration (Table 3.7), the parameters for the weighting functions for gains and losses are 0.535 and 0.551, respectively. As these values are so close, we believe that it is reasonable to use the same parameter in the gain and loss domains (the same argument for using identical specifications of weighting functions for gains and losses also applies to the other examples in this conclusion).

seem intuitively more natural and are more closely aligned with the atemporal literature (they are, for instance, very similar to the estimates of Bruhin, Fehr-Duda, and Epper, 2010).

We also compare these two application methods to a third method, which is similar to the present-value method, but which calculates present values in monetary terms before assigning them a utility value instead of calculating present values directly in utility terms. We consider this a natural way to apply prospect theory when the outcomes are monetary gains and losses (which they usually are; however, prospect theory can also be used with other outcomes, such as consumption levels). For an application of this method, we recommend using the following specifications of a power utility and Goldstein-Einhorn weighting functions, combined with exponential discounting of 4% per quarter:

$$v(x) = \mathbb{1}(x \geq 0)x^{0.92} - \mathbb{1}(x < 0)1.03(-x)^{0.92}, \text{ and } w^+(p) = w^-(p) = \frac{1.04p^{0.40}}{1.04p^{0.40} + (1-p)^{0.40}} \quad (\text{C5}).$$

This specification has very high explanatory power and intuitive parameter estimates.

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3.7 Appendix Paper I

Intertemporal models

This section models farmers decision on adopting a new technology: index insurance. The time horizon is two periods, $t = 1, 2$. Each period's consumption $c(\cdot)$ is a function of the exogenous but stochastic income Y_t and possible insurance indemnity payments. Let $\bar{c}$ stand for the permanent consumption that is assumed to be the same in both periods.¹⁴ Furthermore, $\gamma \in [0, 1]$ is the smoothing parameter that depends on several farmers' characteristics. Finally, according to Deaton (1992), the consumption of a farmer who is limited in his ability to smooth consumption can be approximated by:¹⁵

$$c(Y_t) = \bar{c} + \gamma(Y_t - \mathbb{E}[Y_t]).$$

In the first period the farmer can demand the index insurance for a premium Π . In the second period, the insured farmer receives an indemnity payment Z if the index conditions are fulfilled. Furthermore, outcomes of the second period are discounted. According to recent experimental findings, the discount factor applied by farmers is low. Therefore, we distinguish between the farmer's discount factor δ_f and the market discount factor δ_m and impose the condition $\delta_f < \delta_m$.

In contrast to Carter et al. (2014), we assume that farmers do not obey asset integration. Instead, they evaluate monetary outcomes in terms of gains and losses with respect to some reference point. According to PT, a farmer's value function equals

$$v_t(x) = \begin{cases} (x - r_t)^\alpha & , \text{ if } x \geq r_t \\ -\lambda(r_t - x)^\beta & , \text{ if } x < r_t. \end{cases}$$

r_t is the reference point at time t , α the coefficient of diminishing marginal sensitivity for gains, β the coefficient of diminishing marginal sensitivity for losses and λ the coefficient of loss aversion. Given these model assumptions, a farmer is indifferent between

¹⁴This assumption is reasonable because the time horizon between purchasing the index insurance and possibly receiving a payout is short. As a result, basic consumption needs should not change dramatically.

¹⁵For a farmer with perfect smoothing ability, the consumption in period t is expected to be independent of current resources. This is the case for $\gamma = 0$. If the smoothing parameter takes its maximum value, i.e., $\gamma = 1$, no smoothing is possible and current consumption moves exactly as current income.

demanding and rejecting the insurance, iff

$$v_1[c(Y_1 - \Pi)] + \delta_f \mathbb{E}[v_2[c(Y_2 + Z)]] = v_1[c(Y_1)] + \delta_f \mathbb{E}[v_2[c(Y_2)]] \quad (3.1)$$

The premium Π that solves this implicit equation equals the farmer's (maximum) willingness to pay (WTP). We use the equation to predict how PT preferences impact farmers' WTP within the choice of different reference points. In particular, we distinguish between two groups: farmers with and without a deeper understanding of the insurance. We refer to these as *educated farmers* and *naive farmers*. We assume that naive farmers are not aware of insurance's loss-hedging benefit. Instead, they regard the index insurance as an uncertain investment. A natural reference point to compare the payoffs of an investment to, is the case of not investing at all. Thus, we chose the case of not investing as a naive farmer's reference point and refer to it as *No Insurance Coverage*. Consequently, compared to this reference point, any insurance indemnity payment equals a subjective gain. Furthermore, within this scenario farmers neglect basis risk.¹⁶

In contrast, educated farmers are aware of insurance's loss-hedging benefit. In particular, they expect a full indemnity payment in case of crop failure. Thus, they regard any indemnity payment below the actual value of crop failure as a loss. A natural reference point to model this situation is a *Perfect Insurance*.¹⁷ Due to the possible deviation of the index insurance from a perfect insurance, this scenario includes basis risk.

Reference point: No insurance coverage

A naive farmer's reference point in each period is the income without insurance coverage. Hence, the reference points for $t = 1$ and $t = 2$ are:

$$\begin{aligned} r_1 &= c(Y_1) = \bar{c} + \gamma(Y_1 - \mathbb{E}[Y_1]) = \bar{c} + \gamma\Delta Y_1, \\ r_2 &= c(Y_2) = \bar{c} + \gamma(Y_2 - \mathbb{E}[Y_2]) = \bar{c} + \gamma\Delta Y_2. \end{aligned}$$

¹⁶Farmer without insurance coverage do not receive any indemnity payment in case of crop failure. Thus, a possible non-performance of the index insurance in case of crop failure is not evaluated as a loss.

¹⁷By perfect insurance we refer to an insurance whose indemnity payment always equals the actual value of crop failure.

According to PT, possible outcomes have to be encoded with respect to these reference points.

	$t = 1$			$t = 2$		
insurance	$c(Y_1 - \Pi)$	$-r_1 = -\gamma\Pi < 0$		$c(Y_2 + Z)$	$-r_2 = \gamma Z$	
no insurance	$c(Y_1)$	$-r_1 = 0$		$c(Y_2)$	$-r_2 = 0$	

Table 3.9: Coding of outcomes relative to no insurance coverage

As the table above shows, if an naive farmer rejects insurance, the outcomes correspond to the reference points. As a result, the farmer neither experiences a gain nor a loss. If he, instead, demands the insurance, the premium is considered a loss and the possible payout of the insurance a gain. Due to the nature of the consumption function, these outcomes are multiplied by the smoothing factor γ . Using the value function and the coded outcomes, the equation for the WTP becomes

$$-\lambda(\gamma\Pi)^\beta + \delta_f\gamma^\alpha\mathbb{E}[Z^\alpha] = 0.$$

Therefore, a farmer will demand the insurance, if

$$\Pi \leq \left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha] \right)^{1/\beta}. \quad (3.2)$$

Based on the equation, the following proposition summarizes the predictions for naive farmers.

Proposition 3.7.1 (WTP of naive farmers under Prospect Theory). *Given the reference point 'No insurance coverage', naive farmers' WTP is:*

1. *increasing with the discount factor.*
2. *increasing with the expected subjective valuation of indemnity payments.*
3. *independent of the basis risk.*
4. *decreasing in loss aversion.*

Proof: Appendix 3.7.

In order to derive further insights of naive farmers' index insurance demand, we now focus on one specific scenario. We assume that the farmers and the insurance provider operate on a market in which the following assumption holds.

Assumption 1 (Actuarially fair premium). *A privately owned insurer that operates on the free market will never charge a premium lower than the actuarially fair value $\delta_m \mathbb{E}(Z)$.¹⁸ Typically, a safety loading factor $l > 0$ is added to the premium. Thus, the premium equals $(1 + l) \cdot \delta_m \mathbb{E}(Z)$.*

We first analyze whether a farmer will demand an actuarially fair priced insurance (i.e., $l = 0$). Otherwise, it is straightforward that a privately owned insurer aiming for profit (i.e., $l > 0$), will not generate any demand for its product. For the sake of simplicity, let the diminishing marginal sensitivity for gains and losses be equal, i.e., $\alpha \approx \beta$.¹⁹ A farmer demands a fairly priced insurance product, i.e., $l = 0$, iff

$$\delta_m \mathbb{E}[Z] \leq \left(\frac{\delta_f}{\lambda} \mathbb{E}[Z^\alpha] \right)^{\frac{1}{\alpha}}. \quad (3.3)$$

The inequality can only hold if $\lambda \leq 1$.²⁰ This condition implies that losses do not loom larger than gains and therefore contradicts one of the main and heaviest tested assumptions of PT. Resulting, we state that this condition is never fulfilled.²¹ Therefore, cases in which naive farmers are offered an insurance at a price higher than the actuarially fair value need not to be analyzed as these offers are rejected anyway. Thus, we state the following proposition.

Proposition 3.7.2 (Neglect of insurance among naive farmers). *naive farmers whose reference point is 'No insurance coverage' will not demand insurance offered at or above its actuarially fair value.*

We further analyze the insurance demand if the premium is lower than its actuarially fair value.²² We therefore assume that the following assumptions holds.

Assumption 2 (Subsidy). *With a subsidy factor $s \in (0, 1)$, the insurance premium becomes $\Pi = (1 - s) \cdot \delta_m \mathbb{E}(Z)$.*

¹⁸If an insurer charges a lower premium, then, due to the law of large numbers, it will run out of money eventually.

¹⁹This assumption is supported by Tversky and Kahneman (1992) who find a median value of $\alpha_m = \beta_m = 0.88$.

²⁰Proof: Appendix 3.7.

²¹This implication is straightforward since the naive farmer regards the insurance as an investment and the decision to demand the insurance as being independent of crop risk. Hence, he will not demand a negative return, positive risk insurance contract.

²²A possibility for a premium lower than its actuarially fair value to occur are development subsidies.

A naive farmer will demand the index insurance, iff

$$(1 - s) \cdot \delta_m \mathbb{E}[Z] \leq \left(\frac{\delta_f}{\lambda} \mathbb{E}[Z^\alpha] \right)^{\frac{1}{\alpha}}. \quad (3.4)$$

The following proposition states minimum restrictions for the subsidy s such that an naive farmer demands insurance coverage.

Proposition 3.7.3 (Requirements for the subsidy). *The subsidized insurance is not attractive for an naive farmer if one or both of the inequalities*

$$s \geq 1 - \lambda^{-1/\alpha} \quad (3.5)$$

$$s \geq 1 - \frac{\delta_f}{\delta_m} \quad (3.6)$$

*are not fulfilled. The minimum subsidy requirements are increasing with loss aversion and decreasing with farmer's discount factor.*²³

Proof: Appendix 3.7.

Using the median PT parameters the condition shows that the insurance is not attractive if $s < 0.6$.²⁴ As a result, an naive farmer will not demand the insurance even if the charged premium amounts to only half of its actuarially fair price, i.e., $s = 0.5$. The second condition creates a lower bound with respect to the ratio of the farmer's and market discount factor. Using the median farmer discount factor, $s \geq 0.2$ has to hold.²⁵

Reference Point: Perfect insurance (discrete)

An educated farmer's reference point is a perfect insurance. Thus, due to a possible deviation of the index insurance from the perfect insurance, basis risk enters our model. We define the basis downside risk parameter q and the upside risk parameter q' as the

²³It is important to mention that these conditions are necessary but not sufficient for the inequality to hold.

²⁴The median values $\alpha_m = 0.88, \lambda_m = 2.25$ of Kahneman and Tversky (1979) were estimated in experiments with a small number of students. These populations are among the least representative on a lot of dimensions (Henrich, Heine, and Norenzayan, 2010). However, using PT parameters estimated by Liu (2013) and Holden and Quiggin (2017) in a closer context lead to similar minimum subsidy requirements.

²⁵The market discount factor can, for example, be estimated by using long-term government bond yields. But certainly $\delta_m < 1$ holds. Hence, the condition can be modified to $m \leq \delta_f$. According to Giné, Townsend, and Vickery (2008), the median monthly discount factor applied by farmers is approximately 0.8.

probability that the index insurance underestimates or, respectively, overestimates the actual loss. We further assume that both probabilities are the same, i.e., $q = q'$.²⁶ Therefore, with probability $1 - 2q$ the indemnity payment is correct. Furthermore, as Clarke (2016), we assume that the amount by which the insurance underestimates the crop failure is the same as the amount by which the insurance overestimates it. The following table summarizes the relationship between the perfect insurance Z_2 and the index insurance Z_1 :

Scenario	Probability	Deviation ($Z_1 - Z_2$)
Underestimation of crop failure	q	$-\Delta L$
Accurate estimation	$1 - 2q$	0
Overestimation of crop failure	q	ΔL

Table 3.10: Comparison of perfect and index insurance
Source: Clarke (2016)

We further assume that from a farmer's point of view, the premium of a perfect insurance equals the premium of an index insurance.²⁷ Accordingly, the reference points for $t = 1$ and $t = 2$ are:

$$\begin{aligned} r_1 &= c(Y_1 - \Pi) = \bar{c} + \gamma(Y_1 - \Pi - \mathbb{E}[Y_1]), \\ r_2 &= c(Y_2 + Z_2) = \bar{c} + \gamma(Y_2 + Z_2 - \mathbb{E}[Y_2]). \end{aligned}$$

Recalling, the inequality for the WTP is

$$v_1[c(Y_1 - \Pi)] + \delta_f \mathbb{E}[v_2[c(Y_2 + Z_1)]] \geq v_1[c(Y_1)] + \delta_f \mathbb{E}[v_2[c(Y_2)]]]. \quad (3.7)$$

The following table displays the coding of the outcomes in the two periods:

e	$t = 1$			$t = 2$		
insurance	$c(Y_1 - \Pi)$	$-r_1$	$= 0$	$c(Y_2 + Z_1)$	$-r_2$	$= \gamma(Z_1 - Z_2)$
no insurance	$c(Y_1)$	$-r_1$	$= \gamma\Pi > 0$	$c(Y_2)$	$-r_2$	$= -\gamma Z_2$

Table 3.11: Coding of outcomes relative to perfect insurance

²⁶This assumption corresponds to the findings of Clarke et al. (2012).

²⁷PT aims to reflect a farmer's points of view. Farmers in rural regions of developing countries are not expected to understand that index insurances should entail lower administrative costs. Thus, we deem this assumption reasonable.

If a farmer decides to demand the index insurance, the premium in the first period is equal to the premium of the perfect insurance, and thus, the outcome turns zero. In contrast, if a farmer does not demand the insurance, the farmer saves, relative to the reference point, the premium. Applying the PT value function to the first-period outcomes leads to

$$\begin{aligned} v_1[c(y_1 - \Pi)] &= 0, \\ v_1[c(y_1)] &= (\gamma\Pi)^\alpha. \end{aligned}$$

If a farmer rejects the insurance, he does not receive the possible payout of the perfect insurance in the second period. This leads to

$$\mathbb{E}[v_2[c(Y_2)]] = -\gamma^\beta \lambda \mathbb{E}[Z_2^\beta].$$

In contrast, if he demands the index insurance, the second-period outcome, relative to the reference point, is the deviation of the index insurance payout from the perfect insurance payout. Using the probability weighting function π , the valuation becomes

$$\mathbb{E}[v_2[c(Y_2 + Z_1)]] = \pi(q)[\gamma^\alpha(\Delta L)^\alpha - \gamma^\beta \lambda(\Delta L)^\beta].$$

Plugging these values into the inequality, the index insurance demand condition is given by

$$0 + \delta_f \pi(q) \underbrace{[\gamma^\alpha(\Delta L)^\alpha - \gamma^\beta \lambda(\Delta L)^\beta]}_{:=\otimes} \geq (\gamma\Pi)^\alpha - \delta_f \gamma^\beta \lambda \mathbb{E}[Z_2^\beta].$$

Solving for the premium Π leads to

$$\Pi \leq \frac{\left(\delta_f \pi(q) \otimes + \delta_f \gamma^\beta \lambda \mathbb{E}[Z_2^\beta]\right)^{1/\alpha}}{\gamma}. \quad (3.8)$$

Based on the equation above, the following proposition summarizes the predictions for educated farmers.

Proposition 3.7.4 (WTP of educated farmers under Prospect Theory). *Given the reference point 'Perfect insurance', educated farmers' WTP is:*

1. *increasing with the discount factor.*

2. increasing with the expected subjective valuation of indemnity payments.

3. increasing with the basis risk.

4. increasing with loss aversion.

Proof: see Appendix 3.7.

While the propositions regarding the discount factor and the expected subjective valuation of the indemnity payment coincide with the propositions for the WTP of an educated farmer, the other two show discrepancies.

Reference Point: Perfect insurance (continuous)

We apply the baseline assumption that $Z_1 - Z_2 \sim \mathcal{N}(0, \sigma^2)$. In this case, $\mathbb{E}[Z_1 - Z_2] = 0$. Furthermore, the normal distribution is symmetric, hence, the probability for overestimation is the same as the probability for underestimation and it can represent infinitely many scenarios. Finally, the variance σ^2 represents the basis risk. A higher variance, and therefore higher basis risk leads to higher possible estimation errors. If the basis risk is small, i.e., $\sigma^2 \approx 0$, with high probability only small estimation errors occur.

If an educated farmer demands the insurance, his valuation of the second-period outcome is equal to the expected difference between the index insurance and the perfect insurance. This difference is normally distributed around the mean zero. Therefore, with probability $1/2$ it is positive or negative. As a result, the expected second-period valuation of an educated farmer who purchases the insurance product is equal to:

$$\begin{aligned}\mathbb{E}[v_2[c(Y_2 + Z_2)]] &= \frac{1}{2} \cdot \delta_f \gamma^\alpha \cdot (\sigma^2)^{\alpha/100} f(\alpha) - \frac{1}{2} \cdot \lambda \delta_f \gamma^\alpha \cdot (\sigma^2)^{\alpha/100} f(\alpha) \\ &= \frac{1}{2} \cdot \delta_f \gamma^\alpha \cdot (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha),\end{aligned}$$

where $f(\alpha)$ denotes a strictly positive function depending on the parameter α .²⁸ Using these values, an educated farmer will purchase the insurance product, if

$$0 + \frac{1}{2} \delta_f \gamma^\alpha (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha) \geq (\gamma \Pi)^\alpha - \delta_f \gamma^\alpha \lambda \mathbb{E}[Z_2^\alpha].$$

²⁸Proof: Appendix 3.7.

Consequently, the insurance purchase condition with respect to the premium Π becomes

$$\Pi \leq \left(\frac{1}{2} \delta_f (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha) + \delta_f \lambda \mathbb{E}[Z_2^\alpha] \right)^{1/\alpha}.$$

The inequality above leads to the following Proposition.

Proposition 3.7.5 (WTP of educated farmers under Prospect Theory II). *Given the reference point 'Perfect insurance (continuous)', the WTP of educated farmers is characterized in the following way:*

1. *A higher discount factor leads to a higher WTP.*
2. *A higher expected subjective valuation of the future indemnity payment leads to a higher WTP.*
3. *An increase in the basis risk influences the WTP negatively.*
4. *An increase in loss aversion results into a higher WTP.*

Proof: Appendix 3.7

All propositions correspond to the results in the discrete case. The main difference is that the basis risk parameter and the amount by which an insurance underestimates/overestimates the value of crop failure are captured by one variable: the variance of the normal distribution.

Hence, transforming the discrete scenario from the previous section to a more realistic, continuous representation leaves all important implications unchanged.

Model predictions

This section summarizes the model predictions and compares them to the base model of Carter et al. (2014) and empirical findings. Column (1) of the following table summarizes the predictions of the expected utility model of Carter et al. (2014). Columns (2) and (3) compare these to the predictions of our behavioral model. In line with the base model of Carter et al. (2014), the behavioral model predicts the WTP of both farmer types to be increasing with the discount factor as well as in the expected subjective valuation of the indemnity payment. In contrast to Carter et al. (2014), the behavioral model predicts heterogeneous effects of basis risk and loss aversion among farmer with

different levels of insurance understanding. In particular, basis risk negatively impacts the WTP of an educated farmer whereas it is not related to the WTP of a naive farmer. Furthermore, an increase in loss aversion increases the WTP of an educated farmer and decreases the WTP of a naive farmer.

	Expected Utility Carter et al. (2014)	Prospect Theory		Empirical Findings	
	(1)	Naive	Educated	Naive	Educated
	(1)	(2)	(3)	(4)	(5)
Discount rate	+	+	+	○	○
Expected payout	+	+	+	+	+
Basis risk	—	○	—	○	—
Loss aversion	n.a.	—	+	n.a.	n.a.

Table 3.12: Comparison of rational and behavioral insurance demand model

As displayed by column (4) and (5), a large part of our propositions has already been tested by the empirical literature.²⁹ First, in contrast to our Propositions, Cole et al. (2013) and Giné, Townsend, and Vickery (2008) find index insurance demand to be independent of the discount rate. Second, under the assumption that past average payout in a farmer's village can be used as an approximation of the expected subjective valuation of the indemnity payment, our propositions find support by Cole et al. (2013). Third, recent findings of Jensen, Mude, and Barrett (2018) suggest that deeper understanding of the product increases sensitivity to basis risk considerably. In particular, Jensen, Mude, and Barrett (2018) find only very little relationship between basis risk and demand among farmers that were not further educated about the index insurance.

The only part of our propositions that has not been tested by the empirical literature are Propositions .4 We therefore combine these to our core Hypothesis 3.7.1:

Hypothesis 3.7.1. *The impact of loss aversion on the WTP varies with the level of insurance understanding. While the WTP is increasing with loss aversion among educated farmers it is decreasing with loss aversion among Naive farmers.*

²⁹Instead of measuring farmer's WTP, empirical research mainly focus on observed insurance demand. But, because the market demand curve originates from the premium individuals are willing to pay, the demand is an appropriate measure for the WTP.

Proofs of the intertemporal model (discrete)

Proof of Proposition

The equation for the WTP equals

$$\Pi = \left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha] \right)^{1/\beta}.$$

Calculating the partial derivatives leads to the proofs of the corresponding propositions:

$$\begin{aligned} 1. \quad \frac{\partial \Pi}{\partial \delta_f} &= \underbrace{\frac{1}{\beta} \left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha] \right)^{1/\beta-1}}_{>0} \cdot \underbrace{\frac{1}{\lambda} \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha]}_{>0} > 0 \Rightarrow \text{Prop.1}, \\ 2. \quad \frac{\partial \Pi}{\partial \mathbb{E}(Z^\alpha)} &= \underbrace{\frac{1}{\beta} \left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha] \right)^{1/\beta-1}}_{>0} \cdot \underbrace{\frac{\delta_f}{\lambda} \gamma^{\alpha-\beta}}_{>0} > 0 \Rightarrow \text{Prop.2}, \\ 4. \quad \frac{\partial \Pi}{\partial \lambda} &= \underbrace{\frac{1}{\beta} \left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha] \right)^{1/\beta-1}}_{>0} \cdot \underbrace{-\frac{\delta_f}{\lambda^2} \gamma^{\alpha-\beta} \mathbb{E}[Z^\alpha]}_{<0} < 0 \Rightarrow \text{Prop.4}. \end{aligned}$$

Farmers without insurance coverage do not receive any indemnity payment in case of crop failure. Thus, a possible non-performance of the index insurance in case of crop failure is not evaluated as a loss $\Rightarrow$ Proposition .3. $\square$

Proof of Equation

The discussed inequality equals

$$\delta_m \mathbb{E}(Z) \leq \left[\frac{\delta_f}{\lambda} \mathbb{E}(Z^\alpha) \right]^{1/\alpha}.$$

A few mathematical tools have to be considered: First, PT assumes diminishing marginal sensitivity for losses and gains(i.e., $\alpha < 1$ and $\beta < 1$). Accordingly, Z^α is a concave function and Jensen's inequality is applicable. Second, because of $\delta_f < 1 < \frac{1}{\alpha}$, certainly $(\delta_f)^{1/\alpha} < \delta_f$ has to hold. Finally, the discount rate δ_f applied by the farmers is low. Therefore, $\delta_f < \delta_m$ is assumed. To summarize, the following three inequalities hold:

$$(i) \quad \mathbb{E}(Z^\alpha) \leq [\mathbb{E}(Z)]^\alpha$$

$$(ii) \quad (\delta_f)^{1/\alpha} \leq \delta_f$$

$$(iii) \quad \delta_f \leq \delta_m$$

We show that $\lambda \leq 1$ holds:

$$\begin{aligned} \delta_m \mathbb{E}(Z) &\leq \left[\frac{\delta_f}{\lambda} \mathbb{E}(Z^\alpha) \right]^{1/\alpha} = \left(\frac{\delta_f}{\lambda} \right)^{1/\alpha} (\mathbb{E}(Z^\alpha))^{1/\alpha} \\ &\stackrel{(i)}{\leq} \left[\frac{\delta_f}{\lambda} \right]^{1/\alpha} \cdot \mathbb{E}(Z) = \left(\frac{1}{\lambda} \right)^{1/\alpha} \cdot (\delta_f)^{1/\alpha} \cdot \mathbb{E}(Z) \\ &\stackrel{(ii)}{\leq} \left[\frac{1}{\lambda} \right]^{1/\alpha} \delta_f \cdot \mathbb{E}(Z) \stackrel{(iii)}{\leq} \left[\frac{1}{\lambda} \right]^{1/\alpha} \delta_m \mathbb{E}(Z). \end{aligned}$$

Hence,

$$\delta_m \mathbb{E}[Z] \leq \left(\frac{1}{\lambda} \right)^{1/\alpha} \delta_m \mathbb{E}[Z]$$

has to be satisfied. This is equivalent to

$$1 \leq \left(\frac{1}{\lambda} \right)^{1/\alpha} \Leftrightarrow \lambda \leq 1.$$

□

Proof of Proposition

The inequality discussed is given by

$$(1 - s) \cdot \delta_m \mathbb{E}(Z) \leq \left[\frac{\delta_f}{\lambda} \mathbb{E}(Z^\alpha) \right]^{1/\alpha}.$$

With similar argumentations as in the previous proof, the following inequalities certainly hold:

$$(i) \quad \mathbb{E}(Z^\alpha) \leq [\mathbb{E}(Z)]^\alpha$$

$$(ii) \quad (\delta_f)^{1/\alpha} \leq \delta_f$$

$$(iii) \quad \delta_f \leq \delta_m$$

$$(iv) \quad \left(\frac{1}{\lambda} \right)^{1/\alpha} \leq 1$$

First, $s \geq 1 - \lambda^{-1/\alpha}$ is shown:

$$\begin{aligned}
(1-s) \cdot \delta_m \mathbb{E}(Z) &\leq \left[\frac{\delta_f}{\lambda} \mathbb{E}(Z^\alpha) \right]^{1/\alpha} \\
\Leftrightarrow (1-s) \cdot \delta_m \mathbb{E}(Z) &\leq \left(\frac{1}{\lambda} \right)^{1/\alpha} [\delta_f \mathbb{E}(Z^\alpha)]^{1/\alpha} \stackrel{(i),(ii),(iii)}{\leq} \left(\frac{1}{\lambda} \right)^{1/\alpha} \delta_m \mathbb{E}(Z) \\
\Leftrightarrow (1-s) &\leq \left(\frac{1}{\lambda} \right)^{1/\alpha} \\
\Leftrightarrow s &\geq 1 - \lambda^{-1/\alpha}.
\end{aligned}$$

Second, $s \geq 1 - \frac{\delta_f}{\delta_m}$ is shown:

$$\begin{aligned}
(1-s) \cdot \delta_m \mathbb{E}(Z) &\leq \left[\frac{\delta_f}{\lambda} \mathbb{E}(Z^\alpha) \right]^{1/\alpha} \\
\Leftrightarrow (1-s) \cdot \delta_m \mathbb{E}(Z) &\leq \left(\frac{1}{\lambda} \right)^{1/\alpha} [\delta_f \mathbb{E}(Z^\alpha)]^{1/\alpha} \stackrel{(i),(ii),(iv)}{\leq} 1 \cdot \delta_f \mathbb{E}(Z) \\
\Leftrightarrow (1-s) &\leq \frac{\delta_f}{\delta_m} \\
\Leftrightarrow s &\geq 1 - \frac{\delta_f}{\delta_m}.
\end{aligned}$$

□

Proof of Proposition

Solving for the premium Π leads to

$$\Pi \leq \frac{1}{\gamma} \cdot \left(\underbrace{\delta_f \pi(q) \otimes + \delta_f \gamma^\beta \lambda \mathbb{E}[Z_2^\beta]}_{:= (\star)} \right)^{1/\alpha}. \quad (3.9)$$

For the effect of the subjective valuation, we calculate the derivative of the upper boarder for the premium:

$$\frac{\partial \Pi}{\partial Z_1} = \frac{1}{\alpha \gamma} \underbrace{(\star)^{1/\alpha-1}}_{>0} \cdot \delta_f \cdot \pi(q) \cdot \underbrace{\left[\underbrace{\alpha [\gamma(\Delta L)]^{\alpha-1}}_{>0} \cdot \gamma - \lambda \beta \underbrace{[\gamma(\Delta L)]^{\beta-1}}_{>0} \cdot (-\gamma) \right]}_{>0} > 0.$$

Since we consider the case of positive insurance demand ($\Pi > 0$), $(\star) > 0$ has to hold. $\Rightarrow$ Prop. .2

Since it holds $\otimes < 0$, an increase in the basis risk parameter q leads to a smaller WTP.³⁰ If we again assume $\beta \approx \alpha$,

$$\otimes = \gamma^\alpha (\Delta L)^\alpha [1 - \lambda]$$

holds. As the loss aversion parameter is always larger than one ($\lambda > 1$), an increasing error in estimating ΔL leads to a more negative value of $\otimes$ and therefore to a decreasing WTP. $\Rightarrow$ Prop. .3

The condition, thus, becomes

$$\Pi \leq (\delta_f \pi(q) (\Delta L)^\alpha [1 - \lambda] + \delta_f \lambda \mathbb{E}[Z_2^\alpha])^{1/\alpha}.$$

To analyze the remaining partial derivatives, the following inequalities are needed:

$$(i) \quad \pi(q) (\Delta L)^\alpha > 0$$

$$(ii) \quad \pi(q) (\Delta L)^\alpha = \mathbb{E} \left[(Z_2 - Z_1)^\alpha \mathbb{1}_{\{Z_2 > Z_1\}} \right] \stackrel{Z_1 > 0}{<} \mathbb{E}(Z_2^\alpha).$$

Calculation of the partial derivatives leads to:

$$\frac{\partial \Pi}{\partial \delta_f} = \frac{1}{\alpha} \cdot \delta_f^{1/\alpha - 1} \cdot [\pi(q) (\Delta L)^\alpha + \lambda (\mathbb{E}[Z_2^\alpha] - \pi(q) (\Delta L)^\alpha)]$$

$$\stackrel{(i), (ii)}{>} 0 \Rightarrow \text{Prop. .1,}$$

$$\frac{\partial \Pi}{\partial \lambda} = \frac{1}{\alpha} (\delta_f \pi(q) (\Delta L)^\alpha [1 - \lambda] + \delta_f \lambda \mathbb{E}[Z_2^\alpha])^{1/\alpha - 1} \cdot \delta_f (\mathbb{E}(Z_2^\alpha) - \pi(q) (\Delta L)^\alpha)$$

$$\stackrel{(ii)}{>} 0 \Rightarrow \text{Prop., .4.}$$

□

³⁰According to PT, 'the aggravation one experiences in losing a sum of money appears to be greater than the pleasure associated with gaining the same amount' (Kahneman and Tversky, 1979, p. 279), e.g., $v(x) < -v(-x)$. Now, even when arguing that the insurance's actuaries are approximating the value of crop failure well and therefore conclude that the basis risk parameter is small, the influence of the basis risk should still not be neglected, because, according to PT, small probabilities are often overestimated, i.e., $\pi(q) > q$. Thus, farmers will overestimate small basis risk parameters.

Proofs of the intertemporal model (continuous)

Deviation of $f(\alpha)$

For a random Variable X with density function f_x

$$\mathbb{E}[X^\alpha] = \int_{-\infty}^{\infty} x^\alpha f_x(x) dx.$$

Furthermore, because of $(Z_1 - Z_2) \sim \mathbb{N}(0, \sigma^2)$, the regarded density is given by

$$f_{Z_1 - Z_2} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-x^2}{2\sigma^2}\right).$$

Due to the symmetry of the normal distribution, with probability $\frac{1}{2}$ the difference is negative or positive. For the negative values, following prospect theory, $v(-x) = -\lambda v(x)$ holds. Hence, it holds

$$\begin{aligned} \mathbb{E}[(Z_1 - Z_2)^\alpha] &= \frac{1}{2} \cdot (1 - \lambda) \cdot \int_0^\infty x^\alpha \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-x^2}{2\sigma^2}\right) dx \\ &= \frac{1}{2} \cdot (1 - \lambda) \cdot \frac{(\sigma^2)^{\alpha/100} \cdot \Gamma\left(\frac{1+\alpha}{2}\right)}{2^{1-\alpha/200} \sqrt{\pi}}, \end{aligned}$$

where Γ denotes the Gamma-function with

$$\Gamma(z) = \int_0^\infty t^{z-1} \exp(-t) dt.$$

To conclude:

$$\mathbb{E}[(Z_1 - Z_2)^\alpha] = \frac{1}{2} \cdot (1 - \lambda) (\sigma^2)^{\alpha/100} \cdot f(\alpha),$$

with

$$f(\alpha) = \Gamma\left(\frac{1+\alpha}{2}\right) \frac{1}{2^{1-\alpha/200} \sqrt{\pi}} > 0 \quad \forall \alpha > 0.$$

□

Proof of Proposition

The WTP equals

$$\Pi = \left(\frac{1}{2} \delta_f (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha) + \delta_f \lambda \mathbb{E}[Z_2^\alpha] \right)^{1/\alpha}.$$

The following inequalities hold:

- i) $\frac{1}{2} \cdot (\sigma^2)^{\alpha/100} \cdot f(\alpha) > 0$
- ii) $\frac{1}{2} \cdot (\sigma^2)^{\alpha/100} \cdot f(\alpha) = \mathbb{E} \left[(Z_2 - Z_1)^\alpha \mathbb{1}_{\{Z_2 > Z_1\}} \right] \stackrel{Z_1 > 0}{<} \mathbb{E}[Z_2^\alpha].$

Calculation of the partial derivatives leads to:

$$\begin{aligned} \frac{\partial \Pi}{\partial \delta_f} &= \frac{1}{\alpha} \cdot \delta_f^{(1/\alpha)-1} \cdot \left[\frac{1}{2} (\sigma^2)^{\alpha/100} f(\alpha) + \lambda \left(\mathbb{E}[Z_2^\alpha] - \frac{1}{2} \cdot (\sigma^2)^{\alpha/100} f(\alpha) \right) \right] \stackrel{(i),(ii)}{>} 0, \\ \frac{\partial \Pi}{\partial \lambda} &= \frac{1}{\alpha} \cdot \left(\frac{1}{2} \delta_f (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha) + \delta_f \lambda \mathbb{E}[Z_2^\alpha] \right)^{1/\alpha-1} \\ &\quad \cdot \delta_f \left(\mathbb{E}[Z_2^\alpha] - \frac{1}{2} \cdot (\sigma^2)^{\alpha/100} f(\alpha) \right) \stackrel{(ii)}{>} 0, \\ \frac{\partial \Pi}{\partial \sigma^2} &= \frac{1}{\alpha} \cdot \left(\frac{1}{2} \delta_f (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha) + \delta_f \lambda \mathbb{E}[Z_2^\alpha] \right)^{1/\alpha-1} \\ &\quad \cdot \frac{\alpha}{100} \cdot \frac{1}{2} \delta_f (1 - \lambda) \cdot (\sigma^2)^{\alpha/100-1} f(\alpha) < 0. \end{aligned}$$

□

Appendix 1: Proofs

Proof of Proposition 2.2

Given a subsidized insurance premium, the condition such that a farmer buys the insurance becomes

$$-\lambda(1-p)((1-s)pI)^\alpha + p((1-p(1-s))I)^\alpha \geq 0.$$

This condition can be simplified to

$$\begin{aligned} p((1-p(1-s)))^\alpha &\geq \lambda(1-p)((1-s)p)^\alpha. \\ \Leftrightarrow \frac{p}{1-p} \frac{((1-p(1-s)))^\alpha}{((1-s)p)^\alpha} &\geq \lambda \\ \Leftrightarrow \frac{p}{1-p} \left(\frac{1}{(1-s)p} - 1 \right)^\alpha &\geq \lambda \\ \Leftrightarrow \frac{1}{(1-s)p} - 1 &\geq \left(\lambda \frac{1-p}{p} \right)^{1/\alpha} \\ \Leftrightarrow \frac{1}{(1-s)p} &\geq \left(\lambda \frac{1-p}{p} \right)^{1/\alpha} + 1 \\ \Leftrightarrow \frac{1}{1-s} &\geq p \left(\left(\lambda \frac{1-p}{p} \right)^{1/\alpha} + 1 \right) \\ \Leftrightarrow 1-s &\leq \frac{1}{p \left(\left(\lambda \frac{1-p}{p} \right)^{1/\alpha} + 1 \right)} \\ \Leftrightarrow s &\geq 1 - \frac{1}{p \left(\left(\lambda \frac{1-p}{p} \right)^{1/\alpha} + 1 \right)} \quad \square \end{aligned}$$

Measure of loss aversion: upper and lower bound

(1) Lottery	(2) Loss	(3) Gain	(4) Low. Bound ($\lambda \geq \frac{G_i - G_{i+1}}{L_i - L_{i+1}}$)	(5) Up. Bound ($\lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$)	(6) Low. Bound - Up. Bound
(1)	0	0	$V_1 \geq V_2 \Leftrightarrow \lambda \geq 7$	-	≥ 7
(2)	5	35	$V_2 \geq V_3 \Leftrightarrow \lambda \geq 4$	$V_2 \geq V_1 \Leftrightarrow \lambda \leq 7$	4-7
(3)	10	55	$V_3 \geq V_4 \Leftrightarrow \lambda \geq 3$	$V_3 \geq V_2 \Leftrightarrow \lambda \leq 4$	3-4
(4)	15	70	$V_4 \geq V_5 \Leftrightarrow \lambda \geq 2$	$V_4 \geq V_3 \Leftrightarrow \lambda \leq 3$	2-3
(5)	20	80	$V_5 \geq V_6 \Leftrightarrow \lambda \geq 1$	$V_5 \geq V_4 \Leftrightarrow \lambda \leq 2$	1-2
(6)	25	85	-	$V_6 \geq V_5 \Leftrightarrow \lambda \leq 1$	≤ 1

Table 3.13: Binswanger lotteries

Neglecting probability weighting and assuming that farmers are risk neutral and use the risk-free Lottery (1) as the reference point, the PT Value of Lottery (i) is $V_i = 0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i$, where G_i and L_i denote the loss and the gain associated with Lottery (i); and λ denotes the parameter of loss aversion. The losses and gains associated with each lottery are displayed in Column (2) and (3) of Table 3.13. The aim of this Proof is to show that farmers' choices for Lottery (i) require that $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$ holds.

We start with deriving the lower bound $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda$.

A farmer prefers Lottery (i) over Lottery ($i+1$) if $V_i \geq V_{i+1}$ holds. Using the PT Value, the inequality becomes

$$\begin{aligned}
 0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i &\geq 0.5 \cdot G_{i+1} - \lambda \cdot 0.5 \cdot L_{i+1} \\
 \Leftrightarrow 0.5 \cdot (G_i - G_{i+1}) &\geq \lambda \cdot 0.5 \cdot (L_i - L_{i+1}) \\
 \Leftrightarrow (G_i - G_{i+1}) &\geq \lambda \cdot (L_i - L_{i+1}).
 \end{aligned}$$

Because $L_i - L_{i+1} < 0$ holds for all i , the inequality above can be rearranged to $\lambda \geq \frac{G_i - G_{i+1}}{L_i - L_{i+1}}$.³¹ Column (4) of Table 3.13 displays the loss aversion parameters required such that $V_i \geq V_{i+1}$ holds. The sequence of the parameters is strictly decreasing. Thus, it follows that $V_i \geq V_{i+1}$ implies $V_i \geq V_{i+k} \forall k > 1$.³² Accordingly, it is sufficient to consider the condition $V_i \geq V_{i+1}$ to estimate the lower loss aversion bound associated with farmers' choices for Lottery (i).

³¹Note that the sign of the inequality flipped from $\geq$ into $\leq$ because we divided both sides by the negative term $L_i - L_{i+1}$.

³²A numerical example: $V_1 \geq V_2$ requires $\lambda \geq 7$. $V_2 \geq V_3$ requires $\lambda \geq 4$. Thus, if $V_1 \geq V_2$ is fulfilled, $V_2 \geq V_3$ is also fulfilled. Thus, it follows that $V_1(\geq V_2) \geq V_3$.

The argumentation for the upper bound ($\lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$) is the same.

A farmer prefers Lottery (i) over Lottery ($i - 1$) if $V_i \geq V_{i-1}$ holds. Using the PT Value, the inequality becomes

$$\begin{aligned} 0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i &\geq 0.5 \cdot G_{i-1} - \lambda \cdot 0.5 \cdot L_{i-1} \\ \Leftrightarrow 0.5 \cdot (G_i - G_{i-1}) &\geq \lambda \cdot 0.5 \cdot (L_i - L_{i-1}) \\ \Leftrightarrow (G_i - G_{i-1}) &\geq \lambda \cdot (L_i - L_{i-1}). \end{aligned}$$

Because $L_i - L_{i-1} > 0$ holds for all i , the inequality above can be rearranged to $\lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$. Column (5) displays the loss aversion parameter required such that $V_i \geq V_{i-1}$ holds. Note that the sequence of parameters is again strictly decreasing.³³ Thus, this time it follows that $V_i \geq V_{i-1}$ implies $V_i \geq V_{i-j} \forall j > 1$.³⁴ Accordingly, it is sufficient to consider the condition $V_i \geq V_{i-1}$ to estimate the upper bound associated with farmers' choices of Lottery (i).

To conclude, the lower bound ensures that $V_i \geq V_{i+k}$ holds $\forall k > 0$ and the upper bound ensures that $V_i \geq V_{i-j}$ holds $\forall j > 0$. Thus, the interval between these two bounds ensures that the PT Value of Lottery (i) (weakly) dominates all other lotteries meaning that $V_i \geq V_u$ holds $\forall u \neq i$. The parameter intervals associated with each lottery are displayed in Column (6) of Table 3.13.

Finally, it is not necessary to neglect probability weighting. We can derive the same intervals if we impose the weaker assumption that farmer weight a 0.5-chance for gaining or losing equally ($\pi^+(0.5) = \pi^-(0.5) = \pi(0.5)$). This assumption is, for instance, fulfilled by the probability weighting function proposed by Prelec et al. (1998). Imposing this assumption, $V_i \geq V_{i+1}$ implies $\pi(0.5) \cdot G_i - \lambda \cdot \pi(0.5) \cdot L_i \geq \pi(0.5) \cdot G_{i+1} - \lambda \cdot \pi(0.5) \cdot L_{i+1}$. This can be simplified to $(G_i - G_{i+1}) \geq \lambda \cdot (L_i - L_{i+1})$. Thus, we obtain the same condition as we did when we neglected probability weighting. The same holds for $V_i \geq V_{i-1}$.

State	Loss		No Loss	
	Indemnity (1)	No Indemnity (2)	Indemnity (3)	No Indemnity (4)
Probability	$p(1 - q_1)$	r	r	$(1 - p)(1 - q_2)$
Gains/Losses, No Insurance	$(p - 1)I < 0$	pI	$(p - 1)I$	pI
Gains/Losses, Index Insurance	0	0	0	0

Table 3.14: Index insurance as reference point

Appendix 2: Reference point index insurance

We use $p(1 - q_1) + r = p$ and $r + (1 - p)(1 - q_2) = 1 - p$. Farmers demand index insurance if

$$\begin{aligned}
\underbrace{-\lambda p[(1 - p) \cdot I]^\alpha + (1 - p)(pI)^\alpha}_{\text{value no insurance}} &\leq \underbrace{0}_{\text{value index insurance}} \\
&\Leftrightarrow \frac{(1 - p)(pI)^\alpha}{p(1 - p)^\alpha \cdot I^\alpha} \leq \lambda \\
&\left(\frac{1 - p}{p}\right)^{1 - \alpha} \leq \lambda.
\end{aligned}$$

We can see that an increase in λ makes the condition more likely to be fulfilled.

³³The inequality sign turned from $\geq$ into $\leq$.

³⁴A numerical example: $V_3 \geq V_2$ requires $\lambda \leq 4$. $V_2 \geq V_1$ requires $\lambda \leq 7$. Thus, if $V_3 \geq V_2$ is fulfilled, $V_2 \geq V_1$ is also fulfilled. Thus, it follows that $V_3(\geq V_2) \geq V_1$.

Appendix 3: Behavioral model (only downside basis risk)

We consider an insurance that only possibly underestimates the actual loss. In order to keep the analysis simple, we focus on a model with only three states of the world. A loss L will occur with probability p , no loss with probability $1 - p$. Furthermore, to include the downside basis risk, we assume that given a loss, there is a probability $q_1 > 0$ that the insurance does not pay out the indemnity payment I . We label farmer's initial wealth level with W and, finally, assume that the $\Pi = pI$. Thus, the negative basis risk is not priced in the insurance. The following table summarizes the outcomes for a farmer who demands the insurance and a farmer who does not demand the insurance.

State	Loss		No Loss
	Indemnity	No Indemnity	No Indemnity
	(1)	(2)	(3)
Probability	$p(1 - q_1)$	pq_1	$1 - p$
Gains/Losses, Insurance Cover	$W - pI - L + I$	$W - pI - L$	$W - pI$
Gains/Losses, No Insurance Cover	$W - L$	$W - L$	W

Table 3.15: Four state framework

Reference point no insurance coverage

The following table summarizes the encoded outcomes relative to the first reference point 'No Insurance Coverage':

State	Loss		No Loss
	Indemnity	No Indemnity	No Indemnity
	(1)	(2)	(3)
Probability	$p(1 - q_1)$	r	$1 - p$
Gains/Losses, Insurance Cover	$-pI + I$	$-pI$	$-pI$
Gains/Losses, No Insurance Cover	0	0	0

Table 3.16: Reference point no insurance coverage

Accordingly, a farmer will buy the insurance iff

$$-\lambda(1 - p + r)(pI)^\alpha + p(1 - q_1)((1 - p)I)^\alpha \geq 0.$$

It is obvious that the insurance demand is decreasing with loss aversion and basis risk probability.

Reference point perfect insurance

The following summarizes the encoded outcomes if 'Perfect Insurance' is chosen as a reference point

State	Loss		No Loss
	Indemnity	No Indemnity	No Indemnity
	(1)	(2)	(3)
Probability	$p(1 - q_1)$	r	$1 - p$
Gains/Losses, Insurance Cover	0	$-I$	0
Gains/Losses, No Insurance Cover	$(p - 1)I$	$(p - 1)I$	pI

Table 3.17: Reference point perfect insurance

Accordingly, a farmer will buy the insurance, iff

$$-r\lambda I^\alpha + > -p\lambda((1 - p)I)^\alpha + (1 - p)(pI)^\alpha.$$

Rearranging leads to

$$\lambda(p(1 - p)^\alpha - r) - (1 - p)p^\alpha > 0.$$

It is obvious that the insurance demand is decreasing with the basis risk probability. Furthermore, as in the main model case, the positive impact of loss aversion depends on the condition $p(1 - p)^\alpha > r$ which is most likely fulfilled. Rearranging shows that the loss aversion parameter that is required such that farmers buy the insurance is given by

$$\lambda > \frac{(1 - p)p^\alpha}{(p(1 - p)^\alpha - r)}. \quad (3.10)$$

To recall, in our main model 2.2 the condition such that a farmer buys the insurance equals

$$\lambda(p(1 - p)^\alpha - r) + r - (1 - p)p^\alpha > 0.$$

Rearranging leads to

$$\lambda > \frac{(1-p)p^\alpha}{(p(1-p)^\alpha - r)} - r. \quad (3.11)$$

It is obvious, that this condition is weaker than the other condition. Accordingly, under the existence of only downside basis risk, higher loss aversion levels are required to convince a farmer to buy the insurance.

Appendix 4: Insurance demand and risk aversion

No insurance coverage

Following inequality (2), we know that farmers demand insurance if

$$-\lambda(1-p)(pI)^\alpha + p((1-p)I)^\alpha \geq 0.$$

Rearranging for α leads to

$$\begin{aligned}\lambda &\leq \left(\frac{p}{1-p}\right)^{1-\alpha} \\ \Leftrightarrow \ln_{\frac{p}{1-p}} \lambda &\leq 1 - \alpha \\ \Leftrightarrow \alpha &\leq 1 - \ln_{\frac{p}{1-p}} \lambda.\end{aligned}$$

Therefore, insurance demand is most likely decreasing with risk aversion when using no insurance as reference point.

Perfect insurance

Following inequality (3), we know that farmers demand insurance if

$$r(1-\lambda)I^\alpha > -p\lambda((1-p)I)^\alpha + (1-p)(pI)^\alpha.$$

Rearranging leads to

$$\begin{aligned}\lambda(p(1-p)^\alpha - r) + r - (1-p)p^\alpha &> 0 \\ \Leftrightarrow \lambda p(1-p)^\alpha - \lambda r + r - (1-p)p^\alpha &> 0 \\ \Leftrightarrow r(1-\lambda) &> (1-p)p^\alpha - \lambda p(1-p)^\alpha \\ \frac{r(1-\lambda)}{p(1-p)} &> \underbrace{p^{\alpha-1} - \lambda(1-p)^{\alpha-1}}_{= (*)}.\end{aligned}$$

The smaller $(*) = e^{(\alpha-1)\ln(p)} - \lambda e^{(\alpha-1)\ln(1-p)}$, the more likely the condition is fulfilled:

$$\begin{aligned}
\frac{\partial(*)}{\partial\alpha} &= \ln(p)e^{(\alpha-1)\ln(p)} - \lambda \cdot \ln(1-p)e^{(\alpha-1)\ln(1-p)} \stackrel{!}{<} 0 \\
&\Leftrightarrow \ln(p)p^{\alpha-1} - \lambda \ln(1-p)(1-p)^{\alpha-1} < 0 \\
&\Leftrightarrow \ln(p)p^{\alpha-1} < \lambda \ln(1-p)(1-p)^{\alpha-1} \\
&\Leftrightarrow \underbrace{\lambda \left(\frac{\ln(p)}{\ln(1-p)} \right)}_{>1 \forall p < 0.5} > \underbrace{\left(\frac{1-p}{p} \right)^{\alpha-1}}_{<1 \forall p < 0.5}
\end{aligned}$$

which is a most likely fulfilled condition. Therefore, insurance demand is most likely ($p < 0.5$) increasing with risk aversion when using perfect insurance as reference point.

Appendix 5: Additional tables

	N
Not Visited	347
Visited	700
No Treatment	130
Insurance Education	129
Endorsement	74
High Reward	101
Insurance Education & Endorsement	65
Insurance Education & High Reward	102
Endorsement & High Reward	45
Insurance Education & Endorsement & High Reward	54

Table 3.18: Treatment overview

	Entire Sample Mean (SD)	Insurance Education Mean (SD)	No Insurance Education Mean (SD)	t-test
Take-Up Rate	0.302 (0.459)	0.432 (0.496)	0.236 (0.425)	0.000
Loss Aversion	3.809 (2.195)	3.676 (2.131)	3.875 (2.226)	0.183
Percent of irrigated land	0.417 (0.432)	0.429 (0.437)	0.411 (0.430)	0.544
Above average expected monsoon rain	-0.002 (1.052)	0.046 (1.069)	-0.027 (1.043)	0.319
Insurance demand in 2004 (1=Yes)	0.260 (0.439)	0.248 (0.432)	0.267 (0.443)	0.525
Insurance skills	0.004 (1.000)	0.095 (0.866)	-0.042 (1.058)	0.034
Has other insurance (1=Yes)	0.814 (0.389)	0.819 (0.386)	0.812 (0.391)	0.778
Does not know Basix (1=Yes)	0.294 (0.456)	0.273 (0.446)	0.305 (0.461)	0.303
Belongs to Water User Group (1=Yes)	0.019 (0.137)	0.019 (0.137)	0.019 (0.137)	0.990
No. of community groups	0.740 (0.628)	0.800 (0.639)	0.709 (0.621)	0.039
Belongs to Scheduled Caste/Tribe (1=Yes)	0.112 (0.315)	0.124 (0.330)	0.105 (0.307)	0.410
Muslim (1=Yes)	0.037 (0.189)	0.032 (0.176)	0.040 (0.196)	0.517
Gender (1=Male)	0.946 (0.227)	0.937 (0.244)	0.950 (0.217)	0.406
log household head age	3.855 (0.258)	3.872 (0.250)	3.846 (0.262)	0.136
household size	6.274 (2.826)	6.083 (2.759)	6.371 (2.857)	0.136
High Education (1=Yes)	0.312 (0.464)	0.279 (0.449)	0.329 (0.470)	0.115

Table 3.19: Summary statistics and t-tests

	<i>Dependent variable:</i>				
	'Insurance Take-Up'				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	-0.012** (0.006)	-0.007 (0.006)	-0.016** (0.007)	-0.012* (0.007)	-0.016** (0.008)
Visit (1=Yes)	0.193*** (0.036)	0.192*** (0.035)	0.190*** (0.035)	0.146*** (0.050)	0.146*** (0.050)
Endorsement (1=Yes)	0.060* (0.033)	0.080** (0.035)	0.078** (0.035)	0.060 (0.036)	0.113* (0.063)
High Reward (1=Yes)	0.381*** (0.031)	0.376*** (0.031)	0.381*** (0.031)	0.375*** (0.031)	0.269*** (0.056)
Insurance Education (1=Yes)	-0.006 (0.031)	-0.011 (0.030)	-0.117** (0.054)	-0.113** (0.054)	-0.099* (0.055)
Loss Aversion × Insurance Education			0.029** (0.012)	0.029** (0.012)	0.026** (0.012)
Loss Aversion × Endorsement					-0.013 (0.014)
Loss Aversion × High Reward					0.029** (0.013)
Percent of irrigated land				0.008 (0.033)	0.010 (0.033)
Above average expected monsoon rain				-0.019 (0.013)	-0.021 (0.013)
Insurance demand in 2004 (1=Yes)				0.077** (0.034)	0.076** (0.034)
Insurance skills				-0.004 (0.016)	-0.004 (0.016)
Has other insurance (1=Yes)				0.089*** (0.033)	0.089*** (0.033)
Does not know Basix (1=Yes)				-0.077** (0.031)	-0.076** (0.031)
Belongs to Water User Group (1=Yes)				0.045 (0.094)	0.039 (0.094)
No. of community-groups				0.019 (0.021)	0.016 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014 (0.042)	0.022 (0.042)
Muslim (1=Yes)				-0.023 (0.077)	-0.021 (0.076)
Gender (1=Male)				0.003 (0.057)	0.011 (0.057)
Log household head age				0.059 (0.052)	0.053 (0.052)
Household size				0.003 (0.005)	0.003 (0.005)
High Education (1=Yes)				0.056* (0.030)	0.058* (0.030)
Village Endorsed (1=Yes)				0.065 (0.059)	0.065 (0.059)
Constant	0.090*** (0.032)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.361	0.387	0.391
Adjusted R ²	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.20: Determinants of insurance demand (full table)

	<i>Dependent variable:</i>			
	Insurance Take-Up			
	(1)	(2)	(3)	(4)
Loss Aversion	−0.020*** (0.006)	−0.017*** (0.006)	−0.012* (0.007)	−0.015* (0.008)
Visit (1=Yes)	0.193*** (0.036)	0.191*** (0.036)	0.111** (0.051)	0.112** (0.051)
Endorsement (1=Yes)	0.055 (0.042)	0.068 (0.044)	0.029 (0.047)	0.136* (0.077)
High Reward (1=Yes)	0.384*** (0.040)	0.377*** (0.040)	0.368*** (0.040)	0.249*** (0.068)
Loss Aversion × Endorsement				−0.028* (0.016)
Loss Aversion × High Reward				0.031** (0.015)
Percent of irrigated land			−0.010 (0.037)	−0.012 (0.037)
Above average expected monsoon rain			−0.019 (0.014)	−0.021 (0.014)
Insurance skills			−0.0002 (0.018)	−0.001 (0.018)
Has other insurance (1=Yes)			0.081** (0.037)	0.080** (0.037)
Does not know Basix (1=Yes)			−0.093*** (0.034)	−0.096*** (0.034)
Belongs to Water User Group (1=Yes)			−0.085 (0.105)	−0.088 (0.104)
No. of community-groups			0.049** (0.024)	0.042* (0.024)
Belongs to Scheduled Caste/Tribe (1=Yes)			0.046 (0.048)	0.053 (0.048)
Muslim (1=Yes)			−0.068 (0.079)	−0.067 (0.079)
Gender (1=Male)			−0.031 (0.065)	−0.030 (0.065)
Log household head age			0.035 (0.057)	0.028 (0.057)
Household size			0.002 (0.005)	0.003 (0.005)
High Education (1=Yes)			0.102*** (0.032)	0.103*** (0.032)
Village Endorsed (1=Yes)			0.129** (0.063)	0.129** (0.062)
Constant	0.120*** (0.032)			
Village Fixed Effects	No	Yes	Yes	Yes
Observations	626	626	626	626
Mean Dependent Variable	0.236	0.236	0.236	0.236
R ²	0.320	0.396	0.434	0.440
Adjusted R ²	0.316	0.355	0.381	0.385
Residual Std. Error	0.352	0.341	0.335	0.334

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.21: Determinants of insurance demand (subsample: Farmer who did not receive insurance education)

	<i>Dependent variable:</i>			
	Insurance Take-Up			
	(1)	(2)	(3)	(4)
Loss Aversion	0.005 (0.012)	0.014 (0.012)	0.018 (0.013)	0.010 (0.019)
Endorsement (1=Yes)	0.060 (0.054)	0.100* (0.059)	0.102* (0.060)	0.117 (0.114)
High Reward (1=Yes)	0.386*** (0.053)	0.372*** (0.053)	0.365*** (0.053)	0.285*** (0.106)
Loss Aversion × Endorsement				−0.004 (0.026)
Loss Aversion × High Reward				0.023 (0.026)
Percent of irrigated land			0.120* (0.071)	0.126* (0.072)
Above average expected monsoon rain			−0.011 (0.026)	−0.012 (0.027)
Insurance skills			0.022 (0.035)	0.024 (0.036)
Has other insurance (1=Yes)			0.097 (0.071)	0.099 (0.071)
Does not know Basix (1=Yes)			−0.068 (0.069)	−0.063 (0.070)
Belongs to Water User Group (1=Yes)			0.304 (0.200)	0.298 (0.201)
No. of community-groups			−0.013 (0.042)	−0.011 (0.042)
Belongs to Scheduled Caste/Tribe (1=Yes)			−0.032 (0.088)	−0.020 (0.090)
Muslim (1=Yes)			0.124 (0.202)	0.124 (0.202)
Gender (1=Male)			0.096 (0.110)	0.105 (0.111)
Log household head age			0.027 (0.112)	0.025 (0.112)
Household size			0.008 (0.010)	0.008 (0.010)
High Education (1=Yes)			−0.005 (0.064)	−0.002 (0.064)
Constant	0.211*** (0.063)			
Village Fixed Effects	No	Yes	Yes	Yes
Observations	315	315	315	315
Mean Dependent Variable	0.432	0.432	0.432	0.432
R ²	0.154	0.341	0.377	0.379
Adjusted R ²	0.146	0.247	0.253	0.250
Residual Std. Error	0.459	0.431	0.429	0.430

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.22: Determinants of insurance demand (subsample: Farmer who received insurance education)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.001 (0.006)	0.002 (0.006)	−0.007 (0.008)	−0.008 (0.008)	−0.012 (0.009)
Visit (1=Yes)	0.186*** (0.039)	0.179*** (0.039)	0.178*** (0.039)	0.162*** (0.056)	0.165*** (0.056)
Endorsement (1=Yes)	0.011 (0.036)	0.013 (0.039)	0.012 (0.038)	0.004 (0.041)	0.055 (0.073)
High Reward (1=Yes)	0.447*** (0.034)	0.449*** (0.034)	0.452*** (0.034)	0.449*** (0.035)	0.366*** (0.064)
Insurance Education (1=Yes)	−0.021 (0.034)	−0.020 (0.033)	−0.125** (0.061)	−0.123** (0.062)	−0.121* (0.063)
Loss Aversion × Insurance Education			0.027** (0.013)	0.028** (0.013)	0.028** (0.014)
Loss Aversion × Endorsement					−0.013 (0.015)
Loss Aversion × High Reward					0.022 (0.014)
Percent of irrigated land				−0.013 (0.038)	−0.011 (0.038)
Above average expected monsoon rain				−0.018 (0.014)	−0.019 (0.014)
Insurance skills				−0.008 (0.017)	−0.009 (0.017)
Has other insurance (1=Yes)				0.083** (0.036)	0.083** (0.036)
Does not know Basix (1=Yes)				−0.070** (0.033)	−0.069** (0.033)
Belongs to Water User Group (1=Yes)				−0.009 (0.127)	−0.014 (0.127)
No. of community-groups				0.010 (0.024)	0.007 (0.024)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.016 (0.044)	0.021 (0.044)
Muslim (1=Yes)				0.027 (0.081)	0.028 (0.081)
Gender (1=Male)				−0.020 (0.070)	−0.012 (0.070)
Log household head age				0.058 (0.059)	0.055 (0.059)
Household size				0.003 (0.005)	0.004 (0.005)
High Education (1=Yes)				−0.006 (0.035)	−0.004 (0.035)
Village Endorsed (1=Yes)				0.019 (0.066)	0.018 (0.066)
Constant	0.019 (0.035)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	696	696	696	696	696
Mean Dependent Variable	0.272	0.272	0.272	0.272	0.272
R ²	0.333	0.393	0.397	0.409	0.412
Adjusted R ²	0.328	0.355	0.358	0.357	0.358
Residual Std. Error	0.365	0.358	0.357	0.357	0.357

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.23: Determinants of insurance demand (subsample: Farmer who did not demand insurance in 2004)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	-0.013 (0.008)	-0.007 (0.008)	-0.023** (0.011)	-0.017 (0.011)	-0.034** (0.014)
Endorsement (1=Yes)	0.060 (0.038)	0.069 (0.042)	0.067 (0.042)	0.061 (0.042)	0.094 (0.076)
High Reward (1=Yes)	0.381*** (0.037)	0.372*** (0.036)	0.375*** (0.036)	0.365*** (0.036)	0.207*** (0.069)
Insurance Education (1=Yes)	-0.006 (0.036)	-0.014 (0.035)	-0.150** (0.069)	-0.138** (0.069)	-0.137** (0.069)
Loss Aversion × Insurance Education			0.036** (0.016)	0.036** (0.016)	0.037** (0.016)
Loss Aversion × Endorsement					-0.008 (0.017)
Loss Aversion × High Reward					0.043*** (0.016)
Percent of irrigated land				-0.002 (0.048)	-0.00002 (0.048)
Above average expected monsoon rain				-0.022 (0.018)	-0.024 (0.018)
Insurance demand in 2004 (1=Yes)				0.094** (0.048)	0.095** (0.047)
Insurance skills				0.021 (0.025)	0.023 (0.025)
Has other insurance (1=Yes)				0.103** (0.048)	0.103** (0.048)
Does not know Basix (1=Yes)				-0.092** (0.047)	-0.087* (0.047)
Belongs to Water User Group (1=Yes)				0.042 (0.144)	0.025 (0.143)
No. of community-groups				0.010 (0.030)	0.006 (0.030)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.005 (0.060)	0.023 (0.060)
Muslim (1=Yes)				-0.031 (0.128)	-0.021 (0.127)
Gender (1=Male)				0.024 (0.082)	0.045 (0.082)
Log household head age				0.072 (0.077)	0.063 (0.076)
Household size				0.005 (0.007)	0.006 (0.007)
High Education (1=Yes)				0.060 (0.043)	0.063 (0.043)
Village Endorsed (1=Yes)					
Constant	0.285*** (0.047)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	634	634	634	634	634
Mean Dependent Variable	0.427	0.427	0.427	0.427	0.427
R ²	0.158	0.276	0.283	0.316	0.325
Adjusted R ²	0.153	0.227	0.234	0.251	0.258
Residual Std. Error	0.456	0.435	0.433	0.429	0.427

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.24: Determinants of insurance demand (subsample: Visited farmers)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	-0.021*** (0.006)	-0.017*** (0.006)	-0.023*** (0.007)	-0.020*** (0.007)	-0.019*** (0.007)
Visit (1=Yes)	0.178*** (0.035)	0.158*** (0.034)	0.161*** (0.034)	0.169*** (0.047)	0.169*** (0.047)
Endorsement (1=Yes)	0.098** (0.038)	0.141*** (0.040)	0.138*** (0.039)	0.142*** (0.043)	0.178** (0.075)
Insurance Education (1=Yes)	0.0004 (0.037)	0.008 (0.035)	-0.089 (0.063)	-0.099 (0.063)	-0.105 (0.064)
Loss Aversion × Insurance Education			0.024* (0.013)	0.026** (0.013)	0.028** (0.013)
Loss Aversion × Endorsement					-0.009 (0.015)
Percent of irrigated land				0.010 (0.034)	0.011 (0.034)
Above average expected monsoon rain				-0.016 (0.013)	-0.016 (0.013)
Insurance skills				-0.025 (0.016)	-0.025 (0.016)
Has other insurance (1=Yes)				0.065* (0.033)	0.065** (0.033)
Does not know Basix (1=Yes)				-0.099*** (0.031)	-0.099*** (0.031)
Belongs to Water User Group (1=Yes)				0.044 (0.097)	0.046 (0.097)
No. of community-groups				0.036* (0.021)	0.035 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.008 (0.043)	0.007 (0.043)
Muslim (1=Yes)				0.033 (0.075)	0.033 (0.075)
Gender (1=Male)				-0.011 (0.057)	-0.012 (0.057)
Log household head age				-0.015 (0.053)	-0.016 (0.053)
Household size				-0.003 (0.005)	-0.003 (0.005)
High Education (1=Yes)				0.077** (0.030)	0.078** (0.030)
Village Endorsed (1=Yes)				-0.009 (0.058)	-0.009 (0.058)
Constant	0.124*** (0.031)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	653	653	653	653	653
Mean Dependent Variable	0.153	0.153	0.153	0.153	0.153
R ²	0.108	0.267	0.272	0.312	0.313
Adjusted R ²	0.103	0.219	0.223	0.249	0.248
Residual Std. Error	0.341	0.318	0.318	0.312	0.313

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.25: Determinants of insurance demand (subsample: Farmers who did not receive the high reward)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	-0.013** (0.006)	-0.007 (0.006)	-0.017** (0.008)	-0.013 (0.008)	-0.018** (0.009)
Visit (1=Yes)	0.192*** (0.036)	0.191*** (0.035)	0.189*** (0.035)	0.146*** (0.050)	0.146*** (0.050)
Endorsement (1=Yes)	0.060* (0.033)	0.080** (0.035)	0.078** (0.035)	0.060 (0.036)	0.121* (0.066)
High Reward (1=Yes)	0.381*** (0.031)	0.377*** (0.031)	0.382*** (0.031)	0.375*** (0.031)	0.262*** (0.059)
Insurance Education (1=Yes)	-0.006 (0.031)	-0.011 (0.030)	-0.130** (0.057)	-0.125** (0.057)	-0.110* (0.058)
Loss Aversion × Insurance Education			0.033** (0.013)	0.033** (0.013)	0.030** (0.014)
Loss Aversion × Endorsement					-0.016 (0.015)
Loss Aversion × High Reward					0.031** (0.014)
Percent of irrigated land				0.008 (0.033)	0.010 (0.033)
Above average expected monsoon rain				-0.019 (0.013)	-0.021 (0.013)
Insurance demand in 2004 (1=Yes)				0.077** (0.034)	0.076** (0.034)
Insurance skills				-0.004 (0.016)	-0.004 (0.016)
Has other insurance (1=Yes)				0.090*** (0.033)	0.091*** (0.033)
Does not know Basix (1=Yes)				-0.076** (0.031)	-0.075** (0.031)
Belongs to Water User Group (1=Yes)				0.045 (0.094)	0.039 (0.094)
No. of community-groups				0.019 (0.021)	0.016 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014 (0.042)	0.022 (0.042)
Muslim (1=Yes)				-0.021 (0.076)	-0.020 (0.076)
Gender (1=Male)				0.003 (0.057)	0.010 (0.056)
Log household head age				0.058 (0.052)	0.053 (0.052)
Household size				0.003 (0.005)	0.003 (0.005)
High Education (1=Yes)				0.056* (0.030)	0.058* (0.030)
Village Endorsed (1=Yes)				0.064 (0.059)	0.064 (0.059)
Constant	0.092*** (0.033)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.361	0.387	0.391
Adjusted R ²	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.26: Determinants of insurance demand ($\lambda = 7 + \min(\text{distance}) = 7.5$)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	-0.013** (0.006)	-0.007 (0.006)	-0.017** (0.007)	-0.012 (0.008)	-0.017** (0.009)
Visit (1=Yes)	0.193*** (0.036)	0.191*** (0.035)	0.189*** (0.035)	0.146*** (0.050)	0.146*** (0.050)
Endorsement (1=Yes)	0.060* (0.033)	0.080** (0.035)	0.078** (0.035)	0.060 (0.036)	0.119* (0.065)
High Reward (1=Yes)	0.381*** (0.031)	0.376*** (0.031)	0.381*** (0.031)	0.375*** (0.031)	0.264*** (0.058)
Insurance Education (1=Yes)	-0.006 (0.031)	-0.011 (0.030)	-0.127** (0.057)	-0.122** (0.056)	-0.107* (0.057)
Loss Aversion × Insurance Education			0.032** (0.013)	0.032** (0.013)	0.029** (0.013)
Loss Aversion × Endorsement					-0.015 (0.015)
Loss Aversion × High Reward					0.031** (0.014)
Percent of irrigated land				0.008 (0.033)	0.010 (0.033)
Above average expected monsoon rain				-0.019 (0.013)	-0.021 (0.013)
Insurance demand in 2004 (1=Yes)				0.077** (0.034)	0.076** (0.034)
Insurance skills				-0.004 (0.016)	-0.004 (0.016)
Has other insurance (1=Yes)				0.090*** (0.033)	0.090*** (0.033)
Does not know Basix (1=Yes)				-0.076** (0.031)	-0.075** (0.031)
Belongs to Water User Group (1=Yes)				0.045 (0.094)	0.039 (0.094)
No. of community-groups				0.019 (0.021)	0.016 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014 (0.042)	0.022 (0.042)
Muslim (1=Yes)				-0.022 (0.077)	-0.020 (0.076)
Gender (1=Male)				0.003 (0.057)	0.010 (0.056)
Log household head age				0.058 (0.052)	0.053 (0.052)
Household size				0.003 (0.005)	0.003 (0.005)
High Education (1=Yes)				0.056* (0.030)	0.058* (0.030)
Village Endorsed (1=Yes)				0.064 (0.059)	0.064 (0.059)
Constant	0.091*** (0.033)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.361	0.387	0.391
Adjusted R ²	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.27: Determinants of insurance demand ($\lambda = 7 + \text{mean}(\text{distance}) = 7.75$)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.010*	−0.005	−0.014**	−0.010	−0.013*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
Visit (1=Yes)	0.191***	0.190***	0.188***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.077**	0.059	0.132**
	(0.033)	(0.035)	(0.035)	(0.036)	(0.067)
High Reward (1=Yes)	0.382***	0.377***	0.382***	0.376***	0.268***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.060)
Insurance Education (1=Yes)	−0.005	−0.010	−0.137**	−0.130**	−0.116**
	(0.031)	(0.030)	(0.058)	(0.058)	(0.059)
Loss Aversion × Insurance Education			0.029**	0.029**	0.027**
			(0.011)	(0.011)	(0.012)
Loss Aversion × Endorsement					−0.016
					(0.013)
Loss Aversion × High Reward					0.025**
					(0.012)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.020
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.003	−0.003
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.091***	0.093***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.075**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.046	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.019	−0.019
				(0.076)	(0.076)
Gender (1=Male)				0.004	0.008
				(0.056)	(0.056)
Log household head age				0.056	0.052
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.057*	0.059**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.063	0.062
				(0.059)	(0.059)
Constant	0.087**				
	(0.034)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.360	0.387	0.391
Adjusted R ²	0.275	0.326	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.28: Determinants of insurance demand ($\lambda_{upper\ bound} = 8$)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.010*	−0.005	−0.014**	−0.010	−0.013*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Visit (1=Yes)	0.192***	0.191***	0.188***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.077**	0.059	0.129*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.066)
High Reward (1=Yes)	0.381***	0.377***	0.382***	0.376***	0.269***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.059)
Insurance Education (1=Yes)	−0.006	−0.010	−0.132**	−0.126**	−0.113*
	(0.031)	(0.030)	(0.057)	(0.057)	(0.058)
Loss Aversion × Insurance Education			0.028**	0.028**	0.026**
			(0.011)	(0.011)	(0.011)
Loss Aversion × Endorsement					−0.015
					(0.013)
Loss Aversion × High Reward					0.025**
					(0.012)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.003	−0.003
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.092***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.076**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.046	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.020	−0.020
				(0.076)	(0.076)
Gender (1=Male)				0.004	0.009
				(0.056)	(0.056)
Log household head age				0.057	0.052
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.057*	0.059**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.064	0.063
				(0.059)	(0.059)
Constant	0.087***				
	(0.033)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.360	0.387	0.391
Adjusted R ²	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.29: Determinants of insurance demand ($\lambda_{upper\ bound} = 8.5$)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.009*	−0.005	−0.013**	−0.009	−0.013*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Visit (1=Yes)	0.193***	0.191***	0.189***	0.146***	0.147***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.059	0.119*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.063)
High Reward (1=Yes)	0.381***	0.377***	0.382***	0.375***	0.275***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.055)
Insurance Education (1=Yes)	−0.006	−0.011	−0.119**	−0.114**	−0.101*
	(0.031)	(0.030)	(0.054)	(0.054)	(0.055)
Loss Aversion × Insurance Education			0.024**	0.024**	0.022**
			(0.010)	(0.010)	(0.010)
Loss Aversion × Endorsement					−0.012
					(0.011)
Loss Aversion × High Reward					0.023**
					(0.010)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.090***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.076**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.046	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.022	−0.021
				(0.077)	(0.076)
Gender (1=Male)				0.004	0.010
				(0.057)	(0.056)
Log household head age				0.058	0.052
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.058**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.065	0.064
				(0.059)	(0.059)
Constant	0.087***				
	(0.032)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.360	0.387	0.391
Adjusted R ²	0.275	0.327	0.330	0.347	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.30: Determinants of insurance demand ($\lambda_{upper\ bound} = 10$)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.017** (0.009)	−0.009 (0.009)	−0.026** (0.010)	−0.019* (0.011)	−0.028** (0.012)
Visit (1=Yes)	0.192*** (0.036)	0.191*** (0.035)	0.187*** (0.035)	0.146*** (0.050)	0.146*** (0.050)
Endorsement (1=Yes)	0.060* (0.033)	0.080** (0.035)	0.078** (0.035)	0.059 (0.036)	0.123 (0.083)
High Reward (1=Yes)	0.380*** (0.031)	0.377*** (0.031)	0.382*** (0.031)	0.376*** (0.031)	0.225*** (0.074)
Insurance Education (1=Yes)	−0.005 (0.031)	−0.010 (0.030)	−0.200*** (0.072)	−0.193*** (0.072)	−0.168** (0.073)
Loss Aversion × Insurance Education			0.052*** (0.018)	0.052*** (0.018)	0.045** (0.018)
Loss Aversion × Endorsement					−0.017 (0.021)
Loss Aversion × High Reward					0.042** (0.019)
Percent of irrigated land				0.009 (0.033)	0.010 (0.033)
Above average expected monsoon rain				−0.019 (0.013)	−0.020 (0.013)
Insurance demand in 2004 (1=Yes)				0.078** (0.034)	0.079** (0.034)
Insurance skills				−0.004 (0.016)	−0.004 (0.016)
Has other insurance (1=Yes)				0.090*** (0.033)	0.092*** (0.033)
Does not know Basix (1=Yes)				−0.074** (0.031)	−0.073** (0.031)
Belongs to Water User Group (1=Yes)				0.044 (0.094)	0.038 (0.094)
No. of community-groups				0.018 (0.021)	0.016 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.015 (0.042)	0.024 (0.042)
Muslim (1=Yes)				−0.019 (0.076)	−0.017 (0.076)
Gender (1=Male)				0.003 (0.056)	0.009 (0.056)
Log household head age				0.059 (0.052)	0.054 (0.052)
Household size				0.003 (0.005)	0.003 (0.005)
High Education (1=Yes)				0.056* (0.030)	0.057* (0.030)
Village Endorsed (1=Yes)				0.063 (0.059)	0.063 (0.059)
Constant	0.109*** (0.040)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.362	0.389	0.392
Adjusted R ²	0.276	0.327	0.332	0.349	0.351
Residual Std. Error	0.391	0.377	0.375	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.31: Determinants of insurance demand ($\lambda \in \{1, \dots, 6\}$)

	<i>Dependent variable:</i>		
	Insurance Take-Up		
	(1)	(2)	(3)
Loss Aversion	−0.020*** (0.007)	−0.013* (0.007)	−0.018** (0.008)
Visit (1=Yes)	0.192*** (0.036)	0.182*** (0.040)	0.182*** (0.040)
Endorsement (1=Yes)	0.057* (0.033)	0.058 (0.037)	0.077 (0.064)
High Reward (1=Yes)	0.385*** (0.031)	0.382*** (0.031)	0.298*** (0.056)
Insurance Education (1=Yes)	−0.099* (0.056)	−0.096* (0.055)	−0.082 (0.056)
Loss Aversion × Insurance Education	0.025** (0.013)	0.024* (0.012)	0.021* (0.013)
Loss Aversion × Endorsement			−0.004 (0.014)
Loss Aversion × High Reward			0.023* (0.013)
Percent of irrigated land		0.023 (0.032)	0.022 (0.032)
Above average expected monsoon rain		−0.012 (0.012)	−0.013 (0.012)
Insurance demand in 2004 (1=Yes)		0.061* (0.031)	0.060* (0.031)
Insurance skills		0.025* (0.014)	0.025* (0.014)
Has other insurance (1=Yes)		0.105*** (0.033)	0.104*** (0.033)
Does not know Basix (1=Yes)		−0.084*** (0.029)	−0.083*** (0.029)
Belongs to Water User Group (1=Yes)		0.126 (0.093)	0.121 (0.093)
No. of community-groups		0.028 (0.021)	0.027 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)		0.017 (0.041)	0.024 (0.041)
Muslim (1=Yes)		0.068 (0.067)	0.071 (0.067)
Gender (1=Male)		−0.011 (0.057)	−0.004 (0.057)
Log household head age		0.049 (0.052)	0.045 (0.052)
Household size		0.005 (0.005)	0.005 (0.005)
High Education (1=Yes)		0.027 (0.029)	0.029 (0.029)
Village Endorsed (1=Yes)		−0.002 (0.038)	−0.002 (0.038)
Constant	0.120*** (0.035)	−0.230 (0.212)	−0.203 (0.213)
Observations	941	941	941
Mean Dependent Variable	0.302	0.302	0.302
R ²	0.283	0.323	0.326
Adjusted R ²	0.278	0.308	0.309
Residual Std. Error	0.390	0.382	0.382

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.32: Determinants of insurance demand (regressions without village FE)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.051** (0.023)	−0.051** (0.023)	−0.096*** (0.030)	−0.067** (0.031)	−0.128*** (0.043)
Visit (1=Yes)	1.014*** (0.162)	1.014*** (0.162)	1.022*** (0.163)	1.066*** (0.187)	1.092*** (0.190)
Endorsement (1=Yes)	0.177 (0.111)	0.177 (0.111)	0.168 (0.111)	0.193 (0.135)	0.122 (0.234)
High Reward (1=Yes)	1.008*** (0.106)	1.008*** (0.106)	1.027*** (0.107)	1.097*** (0.112)	0.665*** (0.210)
Insurance Education (1=Yes)	−0.019 (0.106)	−0.019 (0.106)	−0.421** (0.201)	−0.433** (0.210)	−0.407* (0.211)
Loss Aversion × Insurance Education			0.110** (0.046)	0.113** (0.048)	0.112** (0.050)
Loss Aversion × Endorsement					0.025 (0.053)
Loss Aversion × High Reward					0.121** (0.050)
Percent of irrigated land				0.100 (0.129)	0.098 (0.129)
Above average expected monsoon rain				−0.057 (0.049)	−0.060 (0.050)
Insurance demand in 2004 (1=Yes)				0.198 (0.125)	0.197 (0.125)
Insurance skills				0.186*** (0.070)	0.192*** (0.071)
Has other insurance (1=Yes)				0.473*** (0.148)	0.470*** (0.149)
Does not know Basix (1=Yes)				−0.425*** (0.129)	−0.415*** (0.130)
Belongs to Water User Group (1=Yes)				0.477 (0.369)	0.423 (0.370)
No. of community-groups				0.125 (0.084)	0.126 (0.084)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.050 (0.172)	0.097 (0.174)
Muslim (1=Yes)				0.296 (0.284)	0.338 (0.285)
Gender (1=Male)				0.005 (0.235)	0.067 (0.240)
Log household head age				0.175 (0.217)	0.148 (0.218)
Household size				0.019 (0.019)	0.019 (0.019)
High Education (1=Yes)				0.078 (0.117)	0.078 (0.117)
Village Endorsed (1=Yes)				0.012 (0.138)	0.003 (0.138)
Constant	−1.541*** (0.152)	−1.541*** (0.152)	−1.389*** (0.163)	−2.939*** (0.900)	−2.712*** (0.908)
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
Log Likelihood	−433.694	−433.694	−430.596	−399.257	−396.420
Akaike Inf. Crit.	879.388	879.388	875.192	842.515	840.840

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.33: Determinants of Insurance Demand (probit regression)

	<i>Dependent variable:</i>				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Risk Aversion	-0.099** (0.050)	-0.051 (0.049)	-0.156*** (0.060)	-0.123** (0.060)	-0.177** (0.070)
Visit (1=Yes)	0.192*** (0.036)	0.191*** (0.035)	0.187*** (0.035)	0.145*** (0.050)	0.145*** (0.050)
Endorsement (1=Yes)	0.060* (0.033)	0.080** (0.035)	0.078** (0.035)	0.059 (0.036)	0.102 (0.075)
High Reward (1=Yes)	0.380*** (0.031)	0.376*** (0.031)	0.382*** (0.031)	0.376*** (0.031)	0.255*** (0.065)
Insurance Education (1=Yes)	-0.006 (0.031)	-0.010 (0.030)	-0.186*** (0.064)	-0.180*** (0.064)	-0.157** (0.065)
Risk Aversion × Insurance Education			0.316*** (0.102)	0.314*** (0.101)	0.277*** (0.104)
Risk Aversion × Endorsement					-0.072 (0.118)
Risk Aversion × High Reward					0.220** (0.105)
Percent of irrigated land				0.009 (0.033)	0.011 (0.033)
Above average expected monsoon rain				-0.019 (0.013)	-0.020 (0.013)
Insurance demand in 2004 (1=Yes)				0.079** (0.034)	0.080** (0.034)
Insurance skills				-0.004 (0.016)	-0.004 (0.016)
Has other insurance (1=Yes)				0.090*** (0.033)	0.091*** (0.033)
Does not know Basix (1=Yes)				-0.073** (0.031)	-0.071** (0.031)
Belongs to Water User Group (1=Yes)				0.044 (0.094)	0.040 (0.094)
No. of community-groups				0.019 (0.021)	0.016 (0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.016 (0.042)	0.024 (0.042)
Muslim (1=Yes)				-0.021 (0.076)	-0.017 (0.076)
Gender (1=Male)				0.004 (0.056)	0.009 (0.056)
Log household head age				0.060 (0.052)	0.057 (0.052)
Household size				0.003 (0.005)	0.003 (0.005)
High Education (1=Yes)				0.056* (0.030)	0.057* (0.030)
Village Endorsed (1=Yes)				0.064 (0.059)	0.065 (0.059)
Constant	0.100*** (0.037)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R ²	0.279	0.356	0.363	0.390	0.393
Adjusted R ²	0.276	0.327	0.333	0.350	0.352
Residual Std. Error	0.391	0.377	0.375	0.370	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 3.34: Determinants of insurance demand (risk aversion)

3.8 Appendix Paper II

Medicaid: Thresholds and Personal Need Allowance

Figure 3.15 summarizes eligibility thresholds and personal need allowance limits of Medicaid in 2010 and 2021.

State	2021			2010		
	Income Thres.	Asset Thres.	Pers. Need Allow.	Income Thres.	Asset Thres.	Pers. Need Allow.
Alabama	\$2,382	\$2,000	\$30	\$2,022	\$2,000	\$20
Alaska	\$2,382	\$2,000	\$200	\$1,658.04	\$2,000	\$75
Arizona	\$2,382	\$2,000	\$117	\$2,022	\$2,000	\$101
Arkansas	\$2,382	\$2,000	\$40	\$2,022	\$2,000	\$40
California	\$1,481	\$2,000	\$35	\$2,022	\$2,000	\$35
Colorado	\$2,382	\$2,000	\$89.55	\$2,022	\$2,000	\$50
Connecticut	\$2,382	\$1,600	\$60	\$2,022	\$1,600	\$69
Delaware	\$1,985	\$2,000	\$44	\$1,685	\$2,000	\$44
District of Columbia	\$2,382	\$4,000	\$70	\$2,022	\$4,000	\$79
Florida	\$2,382	\$2,000	\$130	\$2,022	\$5,000	\$35
Georgia	\$2,382	\$2,000	\$65	\$2,022	\$2,000	\$50
Hawaii	\$1,235	\$2,000	\$50	\$1,039	\$2,000	\$50
Idaho	\$2,402	\$2,000	\$40	\$2,022	\$2,000	\$40
Illinois	\$1,073	\$2,000	\$30	\$903	\$2,000	\$30
Indiana	\$2,382	\$2,000	\$52	\$2,022	\$2,000	\$52
Iowa	\$2,382	\$2,000	\$50	\$2,022	\$10,000	\$50
Kansas	\$1,157	\$2,000	\$62	\$2,022	\$2,000	\$62
Kentucky	\$2,382	\$2,000	\$40	\$2,022	\$2,000	\$40
Louisiana	\$2,382	\$2,000	\$38	\$2,022	\$2,000	\$38
Maine	\$2,382	\$10,000	\$40	\$2,022	\$2,000	\$40
Maryland	\$2,382	\$2,500	\$82	\$2,022	\$2,000	\$71
Massachusetts	\$1,073	\$2,000	\$72.80	\$2,022	\$2,000	\$73
Michigan	\$2,382	\$2,000	\$60	\$2,022	\$2,000	\$60
Minnesota	\$1,073	\$3,000	\$104	\$2,022	\$3,000	\$89
Mississippi	\$2,382	\$4,000	\$44	\$2,022	\$4,000	\$44
Missouri	\$1,388	\$5,000	\$50	\$1,388	\$5,000	\$30
Montana	\$794	\$2,000	\$50	\$2,022	\$2,000	\$50
Nebraska	\$1,073	\$4,000	\$60	\$2,022	\$4,000	\$50
Nevada	\$2,382	\$2,000	\$35	\$2,022	\$2,000	\$35
New Hampshire	\$2,382	\$2,500	\$70	\$2,022	\$2,500	\$56
New Jersey	\$2,382	\$2,000	\$50	\$2,022	\$4,000	\$35
New Mexico	\$2,382	\$2,000	\$74	\$2,022	\$2,000	\$63
New York	\$884	\$15,750	\$50	\$767	\$13,800	\$50
North Carolina	\$1,073	\$2,000	\$30	\$1,073	\$2,000	\$30
North Dakota	\$891	\$3,000	\$65	\$750	\$3,000	\$50
Ohio	\$2,382	\$2,000	\$50	\$2,022	\$2,000	\$40
Oklahoma	\$2,382	\$2,000	\$50	\$2,022	\$2,000	\$50
Oregon	\$2,382	\$2,000	\$64.11	\$2,022	\$2,000	\$30
Pennsylvania	\$2,382	\$2,400	\$45	\$2,022	\$2,400	\$45
Rhode Island	\$2,382	\$4,000	\$50	\$2,022	\$4,000	\$50
South Carolina	\$2,382	\$2,000	\$30	\$2,022	\$2,000	\$30
South Dakota	\$2,382	\$2,000	\$60	\$2,022	\$2,000	\$60
Tennessee	\$2,382	\$2,000	\$50	\$2,022	\$2,000	\$50
Texas	\$2,382	\$2,000	\$60	\$2,022	\$2,000	\$60
Utah	\$2,382	\$2,000	\$45	\$2,022	\$2,000	\$45
Vermont	\$2,382	\$2,000	\$47.66	\$2,022	\$2,000	\$47.66
Virginia	\$2,382	\$2,000	\$40	\$2,022	\$2,000	\$40
Washington	\$2,382	\$4,000	\$71.12	\$2,022	\$2,000	\$41.62
West Virginia	\$2,382	\$2,000	\$50	\$2,022	\$2,000	\$50
Wisconsin	\$2,382	\$2,000	\$45	\$2,022	\$2,000	\$45
Wyoming	\$2,382	\$2,000	\$50	\$2,022	\$2,000	\$50

Figure 3.15: Medicaid Threshold and Personal Need Allowance 2010 and 2020 by State

Note: This table shows asset and income eligibility thresholds and also the personal need allowance limits of the different states in the U.S. for the years 2010 and 2021. Data are taken from American Council on Aging (2021) and Walker and Accius (2010).

Variable Description

Variable	Definition	Unit
<u>Outcome Variable</u>		
LTCI Demand (1 = Yes)	Indicator for subject's demand for LTCI	0 - 1
<u>Main Explanatory Variables</u>		
Risk Aversion	Elicited Risk Aversion	-0.5 - 1
Ambiguity Aversion	Elicited Ambiguity Aversion	-0.5 - 0.5
Impatience	Elicited Impatience	1 - 4
<u>Mediating Variables</u>		
Insurance Performs (1 = Yes)	Belief about Contract Performance	0 - 1
Bequest Motives (1 = Yes)	Beliefs about Importance of Bequests	0 - 1
No Family Ties (1 = Yes)	Indicator for Family Ties	0 - 1
Care Need (1 = yes)	Beliefs about Care Need	0 - 1
<u>Covariates</u>		
Number of Children	Number of Children living in family	0 - 8
Financial Literacy	Number of correct answers	0 - 3
General Trust	Assessment of trust in people	1 - 4 1: Most people can be trusted, ... 4: Cannot be too careful.
Working (1 = Yes)	Indicator for Working status	0 - 1
Family Income	Income of family in \$ 25,000 baskets	1 - 5 1:< \$25,000, ... ,5:> \$125,000
College (1 = Yes)	Indicator for College Education	0 - 1
Civil Status (1 = Relationship)	Indicator for Relationship	0 - 1
White (1 = Yes)	Indicator for being "White"	0 - 1
Male (1 = yes)	Indicator for being male	0 - 1
Age	Age group of subjects (in 5 year baskets)	1 - 4 1:< 55 years, ... , 4:> 65 years.

Note: The table shows the description of the variables used in this study.

Table 3.35: Variable Description

Additional Data Analysis

3.8.1 Outcome Variable: Self-Insurance

I initially planned to also consider the outcome variable self-insurance. I construct this variable using subject's assessment on a statement in the Brown, Goda, and McGarry (2012) survey about whether he/she has sufficient financial resources to pay for potential LTC expenses. The answer options are "Strongly Disagree", "Disagree", "Neither Disagree nor Agree", "Agree", "Strongly Agree". Table 3.36 shows the distribution of answers. As pre-registered, I set the self-insurance dummy to 1 for subjects who report to either "Agree" or "Strongly Agree". These are 16% of the sample. However, my self-insurance dummy seems to capture savings motives that are unrelated to LTC needs. This is shown in Table 3.37. Neither risk exposure nor beliefs about the performance of the LTC insurance affect the choice to self-insure.

	Strong. Disa.	Disa.	Neither Agree nor Disa.	Agree	Strong. Agree
Means to Self-Insure	0.259	0.348	0.233	0.134	0.024

Note: The table summarizes the distribution of survey responses to the question on self-insurance.

Table 3.36: Responses to Survey Question on Self-Insurance

	Sample Size	Self-Insurance (Mean)
Bequest Motives: Yes	572	0.182
Bequest Motives: No	537	0.132
No Family Ties: Yes	805	0.136
No Family Ties: No	304	0.203
Care Need: Yes	482	0.136
Care Need: No	627	0.172
Insurance Performs: Yes	401	0.157
Insurance Performs: No	708	0.158

Note: The table summarizes the total number of observations and the mean of the outcome variable self-insurance for each of the eight subgroups considered in this study.

Table 3.37: By Group (Self-Insurance)

Survey Questions and Response Distribution

General Information: The Codebook for the survey of Brown et al. (2012) can be downloaded here: <https://alpdata.rand.org/index.php?page=data&p=showsurvey&syid=186>

Demand for LTCI: The following three questions (Q2, Q3 and Q7) are used to measures subject's demand for LTC insurance. The indicator variable LTCI Demand is set to 1 if subjects either answer Q2 or Q7 with "Yes", or Q3 with "It is more likely that I do own a long-term care insurance policy". Otherwise the indicator is set to 0.

Q2: Do you have a long-term care insurance policy?

- Yes.
- No.
- I don't know.

Q3 (Only asked if answer to Q2 is "I don't know"): We realize that you may be uncertain about whether or not you own a long-term care insurance policy, but this information is important to our study. Do you think it is more likely that you do have a long-term care insurance policy, or that you do not?

- It is more likely that I do own a long-term care insurance policy .
- It is more likely that I do not own a long-term care insurance policy.

Q7: Have you ever had an application for long-term care insurance denied?

- Yes.
- No.
- I don't know.

Risk Eposure: The following three questions (Q9, Q10 and Q16) are used as Indicators for different levels of risk exposure. The Indicator for Care Need is set to 1 if the answer to Q9 is either "Strongly Agree" or "Agree". The Indicator for Bequest Motives is set to 1 if the answer to Q11 is either "Strongly Agree" or "Agree". The Indicator Family Ties is set to 1 if the answer to Q16 is neither "Strongly Agree" nor "Agree".

Q9: At some point in the future, it is likely that I will no longer be able to live independently.

- Strongly Disagree.
- Disagree.
- Neither Agree nor Disagree.
- Agree.
- Strongly Agree.

Q10: It is important to me to leave an inheritance to my loved ones.

- Strongly Disagree.
- Disagree.
- Neither Agree nor Disagree.
- Agree.
- Strongly Agree.

Q16: My spouse or another family member will be able to take care of me if I need long-term care.

- Strongly Disagree.
- Disagree.
- Neither Agree nor Disagree.
- Agree.
- Strongly Agree.

Beliefs about Performance of the Insurance: The following two questions (Q24 and Q26) are used to measure subject's beliefs about LTCI performance. The indicator variable "Insurance Performs" is set to 1 if subjects do not answer question Q24 or Q26 with "Agree" or "Strongly Agree" Otherwise the indicator is set to 0.

Q24: I am concerned that an insurance company might deny reasonable claims for long-term care

- Strongly Disagree.
- Disagree.
- Neither Agree nor Disagree.
- Agree.
- Strongly Agree.

Q26: I am concerned that an insurance company may not remain in business long enough to pay for my care

- Strongly Disagree.
- Disagree.
- Neither Agree nor Disagree.
- Agree.
- Strongly Agree.

The distribution of the answers to the survey questions on risk exposure and beliefs about the performance of the insurance is displayed in Table 3.38.

	Strong. Disa.	Disa.	Neither Agree nor Disa.	Agree	Strong. Agree
Family Ties	0.13	0.23	0.36	0.25	0.03
Bequest Motive	0.03	0.13	0.33	0.43	0.08
Care Need	0.05	0.17	0.35	0.37	0.06
Performance I	0.03	0.16	0.33	0.40	0.08
Performance II	0.03	0.15	0.35	0.36	0.11

Note: The table summarizes distribution of responses to the five questions used for the construction of the mediating variables.

Table 3.38: Distribution of Responses to Survey Questions

Comparison of Summary Statistics

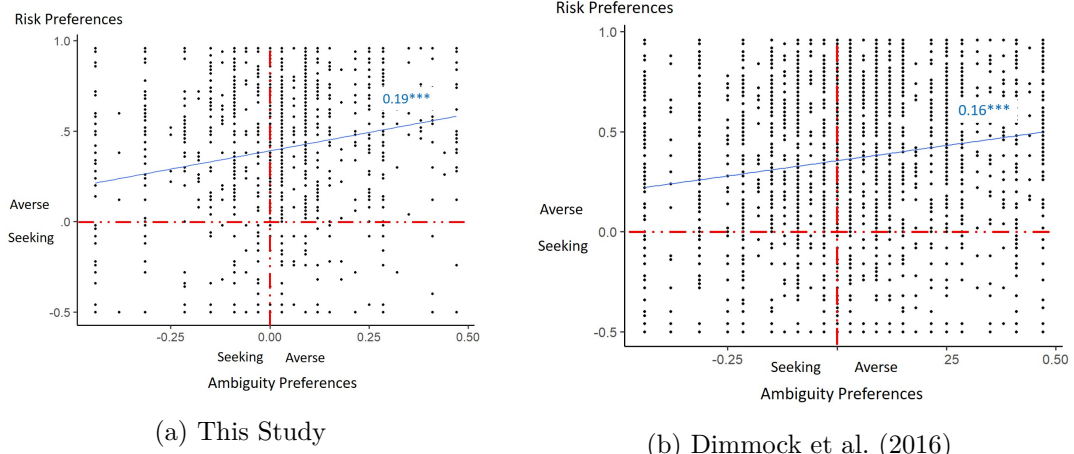
Table 3.39 presents the mean of variables in my sample, the full Dimmock et al. (2016)) sample, and the Brown, Goda, and McGarry (2012) sample. Note that while participants in my sample and the Brown, Goda, and McGarry (2012) sample are 50-years or older, the survey by Dimmock et al. (2016) captures the age range 18 - 70. The results of t-tests that compare the mean of the study sample to those of the single surveys are only statistically significant for the age group comparison with the full Dimmock et al. (2016) survey.

	Study Sample n = 1109	Dimmock (All) n = 3254	Dimmock (Age $\geq$ 50) n = 1633	Brown (All) n = 1621
LTCI (1 = Yes)	0.21	-	-	0.23
Risk Aversion	0.39	0.36	0.39	-
Ambiguity Aversion	0.02	0.02	0.02	-
Insurance Performs (1 = Yes)	0.36	-	-	0.38
Bequest Motives (1 = Yes)	0.51	-	-	0.51
No Family Ties (1 = Yes)	0.73	-	-	0.73
Care Need (1 = yes)	0.43	-	-	0.44
Number of Children	2.10	1.72	2.02	2.22
Financial Literacy	2.19	1.96	2.12	-
General Trust	2.18	2.30	2.22	-
Working (1 = Yes)	0.60	0.62	0.55	0.53
Family Income	3.16	2.78	2.95	3.09
College (1 = Yes)	0.58	0.52	0.54	0.56
Civil Status (1 = Relationship)	0.66	0.60	0.62	0.64
White (1 = Yes)	0.91	0.78	0.85	0.91
Male (1 = yes)	0.41	0.49	0.43	0.42
Age	2.33	1.68***	2.36	2.56

Note: The table shows the mean of the study's variables in the full study sample, the full Dimmock et al. (2016) survey, the group of participants in the Dimmock et al. (2016) that are at least 50 years old, and the full Brown, Goda, and McGarry (2012) study sample. *, **, and *** denote the statistical significance (10-, 5-1, or 1-percent level) of t-test that compare variables in the study sample to those in the other samples.

Table 3.39: Comparison of Mean

Figure 3.16 shows the distribution of risk and ambiguity aversion in my study sample (Panel a) and the sample of the Dimmock et al. (2016) study (Panel b). The distribution of the two parameters in the sample (and also their correlation) is (very similar).



Note: The figure shows the joint distribution of the ambiguity aversion parameter (on the x-axis) and the risk aversion parameter (on the y-axis) in my study sample and the Dimmock et al. (2016) sample. The blue line displays the correlation of these two parameters. The two red lines split the sample into ambiguity (risk) seeking and ambiguity (risk) averse.

Figure 3.16: Distribution Risk and Ambiguity Aversion

Full Regression Tables Main Analysis

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.008 (0.012)			−0.012 (0.012)
Ambiguity Aversion		−0.005 (0.012)		−0.008 (0.013)
Impatience: 2			−0.042 (0.040)	−0.036 (0.040)
Impatience: 3			−0.073** (0.036)	−0.041 (0.037)
Impatience: 4 (Max)			−0.088** (0.037)	−0.036 (0.040)
Bequest Motives (1 = Yes)				0.076*** (0.025)
No Family Ties (1 = Yes)				0.012 (0.028)
Care Need (1 = Yes)				0.097*** (0.025)
Insurance Performs (1 = Yes)				0.100*** (0.026)
Children				−0.010 (0.008)
Financial Literacy				0.009 (0.018)
Trust 2				−0.103*** (0.035)
Trust 3				−0.073** (0.037)
Trust 4				−0.038 (0.204)
Working (1 = Yes)				−0.016 (0.028)
Income 2				0.059 (0.042)
Income 3				0.137*** (0.047)
Income 4				0.058 (0.048)
Income 5				0.127*** (0.047)
College (1 = Yes)				−0.019 (0.027)
Civil Status				−0.016 (0.030)
Ethic				−0.067 (0.045)
Male (1 = Yes)				−0.002 (0.026)
Age 2				0.018 (0.033)
Age 3				0.033 (0.034)
Age 4				0.095** (0.041)
Constant	0.215*** (0.012)	0.215*** (0.012)	0.273*** (0.029)	0.180** (0.088)
Observations	1,109	1,109	1,109	1,109
R ²	0.0004	0.0001	0.006	0.071
Adjusted R ²	−0.001	−0.001	0.003	0.049

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.40: Average Effects (Full Table)

	<i>Dependent variable: LTCI Demand</i>							
	Bequest Motives		No Family Ties		Care Need		Insurance Performs	
	Yes	No	Yes	No	Yes	No	Yes	No
Risk Aversion	-0.012 (0.020)	-0.018 (0.016)	-0.017 (0.015)	-0.023 (0.022)	-0.028 (0.022)	-0.007 (0.015)	-0.045** (0.023)	0.001 (0.015)
Ambiguity Aversion	-0.011 (0.020)	-0.004 (0.017)	-0.031** (0.015)	0.048** (0.024)	-0.022 (0.022)	-0.001 (0.016)	0.012 (0.024)	-0.018 (0.015)
Impatience: 2	-0.025 (0.055)	-0.068 (0.058)	-0.021 (0.045)	-0.023 (0.081)	-0.037 (0.063)	-0.015 (0.052)	-0.124* (0.073)	-0.002 (0.047)
Impatience: 3	-0.047 (0.052)	-0.025 (0.052)	-0.010 (0.043)	-0.072 (0.071)	-0.044 (0.060)	-0.039 (0.047)	-0.131** (0.066)	0.001 (0.044)
Impatience: 4 (Max)	-0.064 (0.061)	0.0003 (0.052)	-0.044 (0.047)	0.050 (0.074)	0.003 (0.065)	-0.051 (0.050)	-0.148** (0.073)	0.003 (0.047)
Bequest Motives (1 = Yes)			0.087*** (0.029)	0.059 (0.048)	0.072* (0.042)	0.074** (0.031)	0.051 (0.047)	0.072** (0.029)
No Family Ties (1 = Yes)	0.029 (0.042)	-0.018 (0.037)			0.029 (0.050)	0.005 (0.033)	0.021 (0.050)	0.015 (0.033)
Care Need (1 = Yes)	0.088** (0.037)	0.109*** (0.034)	0.087*** (0.030)	0.084* (0.048)			0.107** (0.048)	0.086*** (0.029)
Insurance Performs (1 = Yes)	0.097** (0.038)	0.095*** (0.035)	0.100*** (0.030)	0.115** (0.048)	0.108** (0.046)	0.097*** (0.030)		
Children	-0.036*** (0.013)	0.008 (0.010)	-0.024** (0.010)	0.006 (0.012)	0.005 (0.012)	-0.029*** (0.010)	-0.019 (0.015)	-0.004 (0.009)
Financial Literacy	0.033 (0.030)	-0.012 (0.023)	0.019 (0.021)	-0.019 (0.034)	-0.025 (0.032)	0.032 (0.022)	-0.012 (0.031)	0.011 (0.023)
Trust 2	-0.121** (0.048)	-0.071 (0.050)	-0.081** (0.040)	-0.155** (0.067)	-0.136** (0.056)	-0.059 (0.045)	-0.069 (0.059)	-0.131*** (0.042)
Trust 3	-0.095* (0.053)	-0.020 (0.052)	-0.075* (0.043)	-0.050 (0.069)	-0.100* (0.060)	-0.040 (0.047)	-0.097 (0.066)	-0.070 (0.044)
Trust 4	0.098 (0.310)	-0.207 (0.269)	-0.026 (0.236)	-0.015 (0.405)	0.595 (0.447)	-0.244 (0.222)	-0.512 (0.443)	0.070 (0.224)
Working (1 = Yes)	-0.044 (0.041)	0.016 (0.037)	-0.033 (0.032)	0.041 (0.053)	0.013 (0.047)	-0.045 (0.034)	-0.022 (0.050)	-0.022 (0.033)
Income 2	0.012 (0.066)	0.093* (0.052)	0.056 (0.049)	0.064 (0.080)	-0.027 (0.072)	0.121** (0.051)	0.211*** (0.079)	0.003 (0.048)
Income 3	0.159** (0.073)	0.093 (0.060)	0.168*** (0.055)	-0.008 (0.087)	0.139* (0.082)	0.153*** (0.057)	0.175** (0.087)	0.135** (0.055)
Income 4	0.024 (0.074)	0.075 (0.062)	0.034 (0.056)	0.078 (0.089)	0.058 (0.083)	0.055 (0.058)	0.155* (0.089)	0.013 (0.056)
Income 5	0.130* (0.074)	0.119** (0.061)	0.174*** (0.056)	0.005 (0.087)	0.110 (0.082)	0.133** (0.058)	0.178** (0.089)	0.126** (0.055)
College (1 = Yes)	-0.038 (0.041)	0.0004 (0.035)	0.014 (0.031)	-0.133*** (0.050)	0.019 (0.048)	-0.033 (0.032)	0.051 (0.048)	-0.042 (0.032)
Civil Status	0.078* (0.047)	-0.119*** (0.039)	-0.004 (0.036)	-0.026 (0.059)	-0.050 (0.052)	0.008 (0.037)	0.024 (0.055)	-0.032 (0.036)
Ethic	-0.088 (0.073)	-0.013 (0.057)	-0.090 (0.055)	-0.088 (0.079)	-0.041 (0.084)	-0.078 (0.053)	-0.190** (0.080)	-0.002 (0.055)
Male (1 = Yes)	-0.032 (0.038)	0.043 (0.036)	-0.003 (0.030)	0.028 (0.050)	-0.024 (0.044)	0.016 (0.033)	-0.073 (0.047)	0.038 (0.031)
Age 2	0.008 (0.049)	0.015 (0.043)	0.035 (0.038)	-0.047 (0.063)	0.011 (0.056)	0.018 (0.040)	0.047 (0.059)	-0.018 (0.039)
Age 3	0.052 (0.050)	-0.012 (0.046)	0.078* (0.040)	-0.084 (0.066)	0.047 (0.057)	0.020 (0.043)	0.180*** (0.061)	-0.050 (0.040)
Age 4	0.132** (0.062)	0.055 (0.053)	0.171*** (0.048)	-0.075 (0.080)	0.097 (0.069)	0.078 (0.050)	0.286*** (0.072)	-0.022 (0.049)
Constant	0.267* (0.136)	0.144 (0.112)	0.135 (0.100)	0.374** (0.160)	0.311** (0.145)	0.141 (0.110)	0.340** (0.153)	0.173 (0.106)
Observations	572	537	805	304	482	627	401	708
R ²	0.104	0.069	0.115	0.136	0.079	0.081	0.142	0.071

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.41: Heterogeneous Effects (Full Table)

Robustness Checks and Additional Analyses

This section shows the main regression coefficients of my robustness checks. The checks support the conjecture that while risk and ambiguity aversion do not affect insurance demand, impatience has a sizable effect that is most pronounced among subjects with strong risk exposure and subjects who expect the insurance to perform.

Alternative Sample: Table 3.42 and 3.43 summarize the results for the robustness check in which I only include subjects who spent more than 2 minutes on the ambiguity aversion decision tasks (this is my pre-registered sample). Table 3.44 and 3.45 summarize the results for the robustness checks in which I only include subjects who gave consistent answers in the ambiguity aversion check questions. Table 3.46 and 3.47 summarize the results for the robustness check in which I only include subjects with net wealth $> \$10,000$.

Alternative Outcome Variable: Table 3.48 and 3.49 summarize the result in which I set the outcome variable demand for LTCI to 1 for only those subjects who report to have a LTCI. Table 3.50 and 3.51 summarize the result in which I link the survey by Hoffman and Jackson (2013) that asks how likely it is that subjects will demand LTCI in the future.

Alternative Explanatory Variables: Table 3.52 and 3.53 summarize the result in which I use dummy variables for risk and ambiguity aversion. Table 3.55 and 3.56 summarize the result in which I use an alternative specification for risk aversion (self-assessed willingness to take financial risk. Answer options: "I am willing to take substantial financial risks.", "I am willing to take above average financial risks.", "I am willing to take average financial risks.", "I am not willing to take any financial risks."). Table 3.57 and 3.58 summarize the result in which I use an alternative measure for impatience (self assessed planning horizon. Answer options: "The next few months.", "The next year.", "The next few years.", "Longer than 5 years.")

Alternative Grouping: Table 3.59 and 3.60 show the results of the robustness check with a stricter grouping criteria.

Additional Analyses (Further Subsamples): Table 3.61 and 3.62 show the results of additional sample splits (subjects > 65 years old, and subjects with close relatives that staid in a nursing home)

Robustness 1: Decisions Time > 2 Minutes

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.006 (0.013)			−0.009 (0.013)
Ambiguity Aversion		−0.007 (0.013)		−0.011 (0.013)
Impatience: 2			−0.027 (0.041)	−0.021 (0.041)
Impatience: 3			−0.055 (0.037)	−0.023 (0.037)
Impatience: 4 (Max)			−0.075** (0.038)	−0.022 (0.041)
Bequest Motives (1 = Yes)				0.073*** (0.025)
No Family Ties (1 = Yes)				0.017 (0.028)
Care Need (1 = Yes)				0.104*** (0.026)
Insurance Performs (1 = Yes)				0.096*** (0.026)
Constant	0.213*** (0.013)	0.213*** (0.013)	0.258*** (0.030)	0.149* (0.090)
Observations	1,067	1,067	1,067	1,067
R ²	0.0002	0.0003	0.004	0.070
Adjusted R ²	−0.001	−0.001	0.001	0.046

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.42: Average Effects (decision time > 2 minutes)

Panel A: Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.003	-0.013	-0.011	-0.014
	No	-0.012	-0.014	-0.011	-0.006
No Family Ties	Yes	-0.003	-0.01	-0.026	-0.035
	No	-0.016	-0.029	0.042	0.048
Care Need	Yes	-0.013	-0.023	-0.031	-0.025
	No	-0.001	-0.004	0.006	-0.001
Insurance Performs	Yes	-0.023	-0.04	0.01	0.003
	No	0.004	0.003	-0.011	-0.016

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.028	-0.076*	-0.131**	-0.01	-0.025	-0.044
	No	-0.03	-0.013	0.011	-0.053	-0.015	0.01
No Family Ties	Yes	-0.036	-0.057	-0.141**	-0.015	0.001	-0.041
	No	-0.007	-0.037	0.086	0.014	-0.038	0.087
Care Need	Yes	-0.042	-0.077*	-0.043	-0.018	-0.029	0.01
	No	-0.008	-0.041	-0.049	-0.002	-0.021	-0.033
Insurance Performs	Yes	-0.089	-0.129*	-0.147**	-0.094	-0.089	-0.114
	No	0.002	-0.021	-0.039	0.002	0.004	0.004

Note: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCI. *, **,*** denote significance at the 10, 5, and 1-percent level.

Table 3.43: Heterogeneous Effects (decision time > 2 minutes)

Robustness 2: Consistent Responses

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.002 (0.017)			−0.009 (0.017)
Ambiguity Aversion		−0.012 (0.020)		−0.015 (0.021)
Impatience: 2			−0.081 (0.050)	−0.075 (0.050)
Impatience: 3			−0.125*** (0.044)	−0.099** (0.045)
Impatience: 4 (Max)			−0.099** (0.047)	−0.034 (0.051)
Bequest Motives (1 = Yes)				0.082** (0.032)
No Family Ties (1 = Yes)				0.039 (0.037)
Care Need (1 = Yes)				0.089*** (0.032)
Insurance Performs (1 = Yes)				0.077**
Constant	0.215*** (0.016)	0.216*** (0.016)	0.299*** (0.035)	0.127 (0.115)
Further Controls	No	No	No	Yes
Observations	665	665	665	665
R ²	0.00001	0.001	0.012	0.107
Adjusted R ²	−0.001	−0.001	0.008	0.070

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.44: Average Effects (consistent responses)

Panel A: Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.024	-0.041	-0.026	-0.017
	No	0.02	0.01	-0.002	-0.008
No Family Ties	Yes	0.001	-0.015	-0.035	-0.027
	No	-0.008	-0.029	0.048	0.047
Care Need	Yes	-0.025	-0.035	-0.036	-0.038
	No	0.013	0.000	0.001	-0.003
Insurance Performs	Yes	-0.038	-0.065*	0.015	0.015
	No	0.002	0.012	-0.020	-0.024

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.096	-0.149**	-0.19**	-0.096	-0.126**	-0.119
	No	-0.055	-0.071	0.034	-0.065	-0.056	0.041
No Family Ties	Yes	-0.111*	-0.14***	-0.187***	-0.076	-0.08	-0.071
	No	-0.023	-0.098	0.107	0.032	-0.09	0.121
Care Need	Yes	-0.111*	-0.117*	-0.088	-0.091	-0.126	-0.03
	No	-0.056	-0.119	-0.092	-0.024	-0.071	-0.02
Insurance Performs	Yes	-0.154*	-0.168**	-0.127	-0.151*	-0.155*	-0.068
	No	-0.037	-0.097	-0.082	-0.04	-0.084	-0.035

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCL. *, **, *** denote significance 10, 5, and 1-percent level.

Table 3.45: Heterogeneous Effects (consistent responses)

Robustness 3: Net Wealth > 10.000

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.012 (0.014)			−0.019 (0.014)
Ambiguity Aversion		−0.001 (0.014)		−0.004 (0.015)
Impatience: 2			−0.032 (0.043)	−0.027 (0.043)
Impatience: 3			−0.062 (0.039)	−0.030 (0.040)
Impatience: 4 (Max)			−0.073* (0.042)	−0.035 (0.044)
Bequest Motives (1 = Yes)				0.070** (0.028)
No Family Ties (1 = Yes)				0.012 (0.031)
Care Need (1 = Yes)				0.095*** (0.028)
Insurance Performs (1 = Yes)				0.114*** (0.028)
Constant	0.230*** (0.014)	0.230*** (0.014)	0.276*** (0.031)	0.174* (0.105)
Observations	928	928	928	928
R ²	0.001	0.00001	0.004	0.084
Adjusted R ²	−0.0003	−0.001	0.001	0.057

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.46: Average Effects (net wealth > 10.000)

Panel A: Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.005	-0.015	-0.005	-0.008
	No	-0.023	-0.026	-0.008	0.005
No Family Ties	Yes	-0.013	-0.022	-0.028	-0.031
	No	-0.012	-0.02	0.063	0.069
Care Need	Yes	-0.032	-0.042	-0.023	-0.021
	No	0	-0.01	0.01	0.001
Insurance Performs	Yes	-0.035	-0.062	0.025	0.024
	No	0.001	-0.001	-0.011	-0.018

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.023	-0.083*	-0.137**	-0.007	-0.03	-0.065
	No	-0.047	-0.024	0.017	-0.071	-0.026	-0.001
No Family Ties	Yes	-0.03	-0.057	-0.129**	-0.011	-0.002	-0.053
	No	-0.051	-0.065	0.051	0.002	-0.043	0.082
Care Need	Yes	-0.037	-0.059	-0.094*	-0.031	-0.043	-0.076
	No	-0.029	-0.051	-0.026	-0.014	-0.02	0.038
Insurance Performs	Yes	-0.123	-0.172**	-0.16**	-0.139*	-0.146**	-0.182**
	No	0.015	-0.003	-0.029	0.025	0.028	0.02

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCI. *, **,*** denote significance at the 10, 5, and 1-percent level.

Table 3.47: Heterogeneous Effects (net wealth > 10.000)

Robustness 4: Alternative Outcome Variable (1 = Yes)

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	0.0004 (0.011)			−0.006 (0.011)
Ambiguity Aversion		0.007 (0.011)		0.002 (0.011)
Impatience: 2			−0.037 (0.036)	−0.029 (0.035)
Impatience: 3			−0.071** (0.032)	−0.038 (0.033)
Impatience: 4 (Max)			−0.108*** (0.033)	−0.050 (0.035)
Bequest Motives (1 = Yes)				0.060*** (0.022)
No Family Ties (1 = Yes)				0.010 (0.025)
Care Need (1 = Yes)				0.071*** (0.022)
Insurance Performs (1 = Yes)				0.080*** (0.023)
Constant	0.161*** (0.011)	0.161*** (0.011)	0.222*** (0.026)	0.091 (0.078)
Observations	1,109	1,109	1,109	1,109
R ²	0.00000	0.0004	0.011	0.083
Adjusted R ²	−0.001	−0.001	0.008	0.061

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.48: Average Effect (alternative outcome; 1 = Yes)

Panel A: Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.019	-0.028	0	-0.003
	No	0.012	0.012	0.006	0.001
No Family Ties	Yes	-0.003	-0.013	-0.009	-0.017
	No	0.005	-0.005	0.046	0.053
Care Need	Yes	-0.015	-0.024	-0.018	-0.018
	No	0.01	0.001	0.022	0.015
Insurance Performs	Yes	-0.018	-0.034	0.024	0.018
	No	0.011	0.007	0.001	-0.006

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.046	-0.087*	-0.141**	-0.031	-0.039	-0.061
	No	-0.025	-0.038	-0.044	-0.033	-0.024	-0.025
No Family Ties	Yes	-0.029	-0.075*	-0.158***	-0.008	-0.02	-0.059
	No	-0.077	-0.053	0.015	-0.049	-0.042	0.027
Care Need	Yes	-0.074	-0.116**	-0.122**	-0.056	-0.084	-0.042
	No	0.005	-0.016	-0.072	0.009	0.001	-0.035
Insurance Performs	Yes	-0.079	-0.169***	-0.16***	-0.092	-0.134**	-0.12*
	No	-0.015	-0.017	-0.079	-0.007	0.009	-0.031

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCI. *, **,*** denote significance at the 10, 5, and 1-percent level.

Table 3.49: Heterogeneous Effects (alternative outcome; 1 = Yes)

Robustness 5: Alternative Outcome Variable (Probability to Buy Insurance)

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.0004 (0.016)			−0.007 (0.016)
Ambiguity Aversion		−0.008 (0.016)		−0.008 (0.017)
Impatience: 2			0.029 (0.051)	0.027 (0.050)
Impatience: 3			−0.046 (0.046)	−0.014 (0.047)
Impatience: 4 (Max)			−0.053 (0.048)	0.005 (0.051)
Bequest Motives (1 = Yes)				0.047 (0.032)
No Family Ties (1 = Yes)				0.039 (0.036)
Care Need (1 = Yes)				0.141*** (0.032)
Insurance Performs (1 = Yes)				0.104*** (0.033)
Constant	0.218*** (0.016)	0.218*** (0.016)	0.242*** (0.037)	0.137 (0.111)
Observations	683	683	683	683
R ²	0.00000	0.0003	0.006	0.101
Adjusted R ²	−0.001	−0.001	0.002	0.066

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.50: Average Effect (probability to buy insurance)

Panel A: Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.004	-0.014	0.001	0.004
	No	-0.001	-0.001	-0.021	-0.011
No Family Ties	Yes	-0.011	-0.02	-0.017	-0.017
	No	0.017	-0.007	0.009	0.002
Care Need	Yes	0.012	-0.005	-0.032	-0.037
	No	-0.011	-0.014	0.006	0.007
Insurance Performs	Yes	-0.016	-0.044	-0.001	-0.002
	No	0.009	0.004	-0.006	-0.009

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.013	-0.075*	-0.111*	0.025	-0.011	-0.006
	No	0.051	-0.002	0.03	0.039	0.001	0.034
No Family Ties	Yes	-0.004	-0.027	-0.115**	0.071	0.053	-0.003*
	No	-0.063	-0.083	0.086	-0.025	-0.084	0.112
Care Need	Yes	0.008	-0.06	-0.074*	0.01	-0.049	-0.052
	No	0.063	-0.01	0.01	0.084	0.016	0.079
Insurance Performs	Yes	-0.063	-0.116*	-0.14*	-0.089	-0.098	-0.124
	No	0.074	-0.011	-0.009	0.07	0.014	0.045

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCI. *, **,*** denote significance at the 10, 5, and 1-percent level.

Table 3.51: Heterogeneous Effects (probability to buy insurance)

Robustness 6: Dummies for Risk and Ambiguity Aversion

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.033 (0.033)			−0.050 (0.033)
Ambiguity Aversion		0.014 (0.025)		0.007 (0.025)
Impatience: 2			−0.042 (0.040)	−0.036 (0.040)
Impatience: 3			−0.073** (0.036)	−0.038 (0.037)
Impatience: 4 (Max)			−0.088** (0.037)	−0.036 (0.040)
Bequest Motives (1 = Yes)				0.075*** (0.025)
No Family Ties (1 = Yes)				0.013 (0.028)
Care Need (1 = Yes)				0.097*** (0.025)
Insurance Performs (1 = Yes)				0.101*** (0.026)
Constant	0.242*** (0.030)	0.208*** (0.018)	0.273*** (0.029)	0.224** (0.091)
Observations	1,109	1,109	1,109	1,109
R ²	0.001	0.0003	0.006	0.072
Adjusted R ²	−0.00001	−0.001	0.003	0.050

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.52: Average Effects (dummies risk and ambiguity aversion)

Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.034	-0.041	0.006	-0.003
	No	-0.047	-0.056	0.002	0.008
No Family Ties	Yes	-0.056	-0.093	-0.016	-0.026
	No	0.013	0.004	0.091	0.09
Care Need	Yes	-0.055	-0.069	-0.037	-0.026
	No	-0.023	-0.041	0.046	0.026
Insurance Performs	Yes	-0.124	-0.162	0.034	0.022
	No	0.022	0.003	0.007	-0.002

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion. The dependent variable in each of the regressions is subject's demand for LTCI. *, **, *** denote significance at the 10, 5, and 1-percent level.

Table 3.53: Heterogeneous Effects (dummies risk and ambiguity aversion)

Robustness 7: Willingness to Take Financial Risk

Demand for LTCI: I use the following survey question of the Yoong et al. (2019) survey to construct a subjective measure of risk aversion.

Q52: Which of the following statements comes closest to describing the amount of financial risk that you are willing to take when you save or make investments?

- 1: I am willing to take substantial financial risks expecting to earn substantial returns.
- 2: I am willing to take above average financial risks expecting to earn above average returns.
- 3: I am willing to take average financial risks expecting to earn average returns.
- 4: I am not willing to take any financial risks.

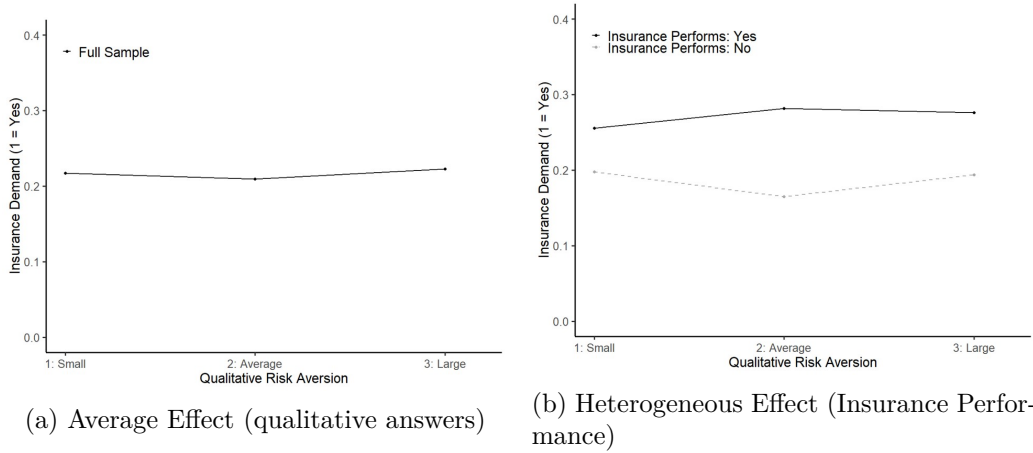
Table 3.54 displays the distribution of responses. Considering that only very few people chose the first answer option, I aggregate the first and second answer option into one category (weak risk aversion). Subjects giving the third answer are subjects classified as average risk averse, and subjects giving the fourth answer are classified as strongly risk averse.

Figure 3.17 shows a visual inspection for the average effect of the qualitative risk aversion measure, and also the heterogeneous effect with respect to insurance performance.

	1	2	3	4	
Willingness to take Financial Risk	0.026	0.213	0.487	0.272	0.03

Table 3.54: Distribution of Responses (Qualitative Risk Aversion Measure)

Figure 3.18 hows a visual inspection for the heterogeneous effect with respect risk exposure. There seems to be no relationship between risk aversion and LTC demand. Even among subjects with strong risk exposure and subjects who expect the insurance to perform risk aversion seems to be unrelated to LTC demand. This finding is also supported by the regression coefficients that are displayed in Table 3.55 and Table 3.56.

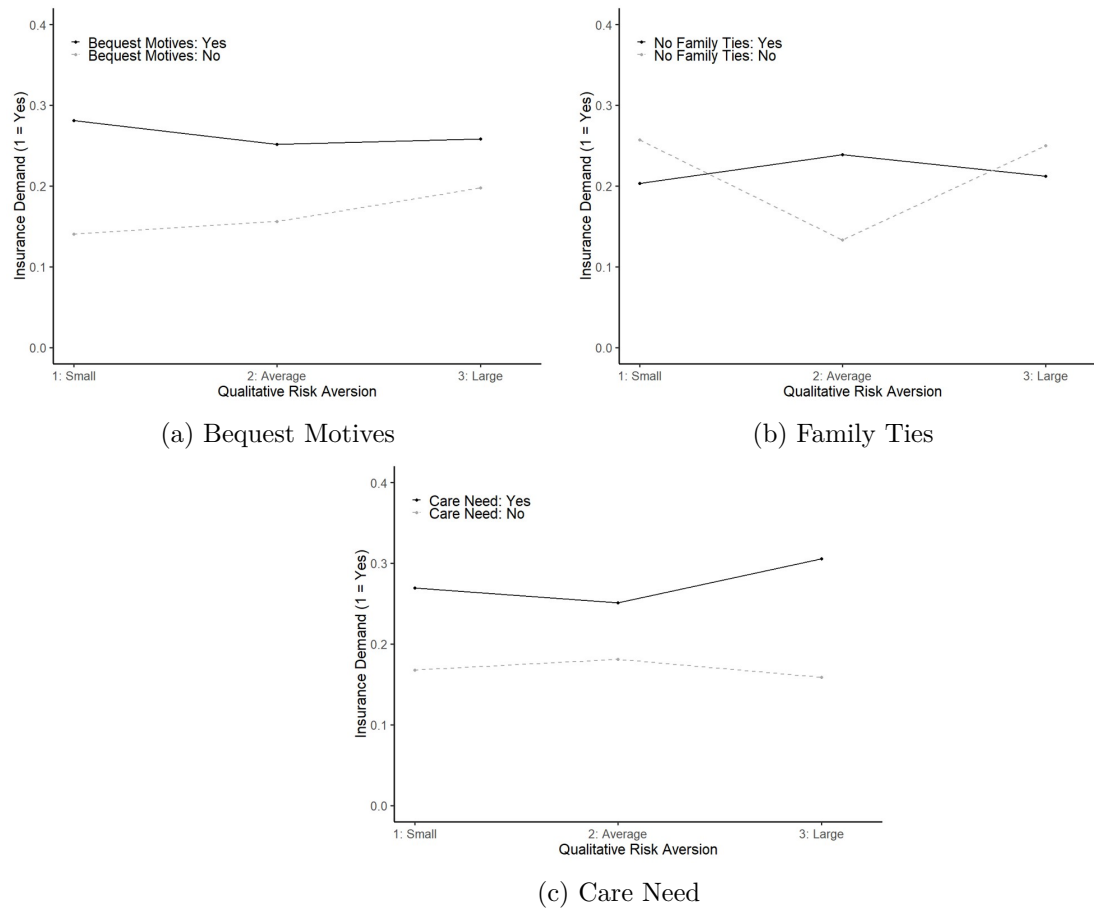


Notes: The figures display average LTC insurance demand rate by risk aversion deciles, ambiguity aversion deciles, and four impatience levels. The lines distinguish between subjects who do and who do not expect the insurance to perform.

Figure 3.17: Average Effect and Heterogenous Effect (Insurance Performance)

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion: 2	−0.008 (0.031)			0.003 (0.031)
Risk Aversion: 3	0.005 (0.035)			−0.056 (0.040)
Ambiguity Aversion		−0.005 (0.012)		−0.008 (0.013)
Impatience: 2			−0.042 (0.040)	−0.036 (0.040)
Impatience: 3			−0.073** (0.036)	−0.040 (0.037)
Impatience: 4 (Max)			−0.088** (0.037)	−0.036 (0.040)
Bequest Motives (1 = Yes)				0.076*** (0.025)
No Family Ties (1 = Yes)				0.013 (0.028)
Care Need (1 = Yes)				0.097*** (0.025)
Insurance Performs (1 = Yes)				0.100*** (0.026)
Constant	0.215*** (0.012)	0.215*** (0.012)	0.273*** (0.029)	0.180** (0.088)
Observations	1,108	1,108	1,108	1,108
R ²	0.0003	0.0001	0.006	0.071
Adjusted R ²	−0.001	−0.001	0.003	0.049
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

Table 3.55: Average Effects (consistent responses)



Notes: The figures display average LTC insurance demand rate by risk aversion deciles, ambiguity aversion deciles, and four impatience levels. The lines distinguish between subjects who do and who do not expect the insurance to perform.

Figure 3.18: Heterogeneous Effects (Insurance Performance)

Qualitative Risk Aversion		Univariate		Multivariate	
		2	3 (Max)	2	3 (Max)
Bequest Motives	Yes	-0.029	-0.023	-0.030	0.008
	No	0.016	0.057	0.041	-0.081
No Family Ties	Yes	0.036	0.009	-0.026	-0.031
	No	-0.124***	-0.007	-0.0949	-0.003
Care Need	Yes	-0.018	0.036	-0.015	0.067
	No	0.0013	-0.009	0.022	0.048
Insurance Performs	Yes	0.026	0.021	-0.001	0.005
	No	-0.033	-0.004	0.009	0.071

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion. The dependent variable in each of the regressions is subject's demand for LTCI. *, **, *** denote significance at the 10, 5, and 1-percent level.

Table 3.56: Heterogeneous Effects (consistent responses)

Robustness 8: Alternative Time Discounting

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.008 (0.012)			−0.012 (0.012)
Ambiguity Aversion		−0.005 (0.012)		−0.008 (0.013)
Impatience: 2			−0.042 (0.040)	−0.036 (0.040)
Impatience: 3			−0.073** (0.036)	−0.041 (0.037)
Impatience: 4 (Max)			−0.088** (0.037)	−0.036 (0.040)
Bequest Motives (1 = Yes)				0.076*** (0.025)
No Family Ties (1 = Yes)				0.012 (0.028)
Care Need (1 = Yes)				0.097*** (0.025)
Insurance Performs (1 = Yes)				0.100*** (0.026)
Constant	0.215*** (0.012)	0.215*** (0.012)	0.273*** (0.029)	0.180** (0.088)
Observations	1,109	1,109	1,109	1,109
R ²	0.0004	0.0001	0.006	0.071
Adjusted R ²	−0.001	−0.001	0.003	0.049

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.57: Average Effects (alternative time discounting)

Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.037	-0.093*	-0.139**	-0.025	-0.047	-0.064
	No	-0.051	-0.035	-0.007	-0.068	-0.026	-0.001
No Family Ties	Yes	-0.042	-0.067*	-0.139**	-0.021	-0.011	-0.044
	No	-0.053	-0.084	0.032	-0.023	-0.072	0.05
Care Need	Yes	-0.058	-0.067*	-0.092*	-0.037	-0.045	0.002
	No	-0.023	-0.052	-0.067	-0.015	-0.039	-0.051
Insurance Performs	Yes	-0.113	-0.161**	-0.17**	-0.124	-0.131**	-0.148**
	No	-0.005	-0.027	-0.044	-0.002	0.001	0.003

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCI. *, **,*** denote significance at the 10, 5, and 1-percent level.

Table 3.58: Heterogeneous Effect (alternative time discounting)

Robustness 9: Alternative Grouping

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.008 (0.012)			−0.014 (0.012)
Ambiguity Aversion		−0.005 (0.012)		−0.007 (0.013)
Impatience: 2			−0.042 (0.040)	−0.041 (0.040)
Impatience: 3			−0.073** (0.036)	−0.048 (0.037)
Impatience: 4 (Max)			−0.088** (0.037)	−0.045 (0.040)
Bequest Motives (1 = Yes)				0.075* (0.044)
No Family Ties (1 = Yes)				0.052* (0.027)
Care Need (1 = Yes)				0.017 (0.050)
Insurance Performs (1 = Yes)				0.193*** (0.047)
Constant	0.215*** (0.012)	0.215*** (0.012)	0.273*** (0.029)	0.247*** (0.085)
Observations	1,109	1,109	1,109	1,109
R ²	0.0004	0.0001	0.006	0.060
Adjusted R ²	−0.001	−0.001	0.003	0.037
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

Table 3.59: Average Effects (alternative grouping)

Panel A: Risk and Ambiguity Aversion

		Risk Av.		Amb. Av.	
		Univ.	Multiv.	Univ.	Multiv.
Bequest Motives	Yes	-0.052	-0.072	0.011	-0.039
	No	-0.005	-0.009	-0.008	-0.008
No Family Ties	Yes	-0.021	-0.038	-0.025	-0.02
	No	-0.002	-0.005	0.007	0.003
Care Need	Yes	0.031	-0.009	-0.061	-0.035
	No	-0.011	-0.018	-0.001	-0.005
Insurance Performs	Yes	-0.007	0	0.007	-0.058
	No	-0.01	-0.014	-0.005	-0.006

Panel B: Impatience

		Univariate			Multivariate		
		2	3	4 (max)	2	3	4 (max)
Bequest Motives	Yes	-0.355**	-0.27**	-0.355**	-0.251*	-0.195	-0.297*
	No	-0.004	-0.046	-0.054	-0.005	-0.021	-0.012
No Family Ties	Yes	-0.048	-0.073	-0.207***	-0.04	-0.021	-0.115*
	No	-0.051	-0.075	-0.026	-0.054	-0.061	-0.013
Care Need	Yes	0	-0.175*	-0.214*	-0.051	-0.225	-0.277
	No	-0.044	-0.066	-0.079	-0.045	-0.04	-0.04
Insurance Performs	Yes	-0.323**	-0.295*	-0.56***	-0.381**	-0.431**	-0.393**
	No	-0.027	-0.059	-0.053	-0.021	-0.033	-0.026

Notes: The table shows univariate and multivariate regression coefficients for (standardized) risk and ambiguity aversion (Panel A), and the three impatient dummies (Panel B). The dependent variable in each of the regressions is subject's demand for LTCI. *, **,*** denote significance at the 10, 5, and 1-percent level.

Table 3.60: Heterogeneous Effects (alternative grouping)

Robustness 10: Age > 65

<i>Dependent variable: LTCI Demand</i>				
	(1)	(2)	(3)	(4)
Risk Aversion	0.027 (0.030)			−0.009 (0.013)
Ambiguity Aversion		0.010 (0.034)		−0.011 (0.013)
Impatience: 2			0.014 (0.098)	−0.021 (0.041)
Impatience: 3			−0.048 (0.090)	−0.023 (0.037)
Impatience: 4 (Max)			−0.095 (0.092)	−0.022 (0.041)
Bequest Motives (1 = Yes)				0.073*** (0.025)
No Family Ties (1 = Yes)				0.017 (0.028)
Care Need (1 = Yes)				0.104*** (0.026)
Insurance Performs (1 = Yes)				0.096*** (0.026)
Constant	0.274*** (0.032)	0.276*** (0.033)	0.311*** (0.067)	0.149* (0.090)
Observations	193	193	193	1,067
R ²	0.004	0.0004	0.009	0.070
Adjusted R ²	−0.001	−0.005	−0.007	0.046

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.61: Average Effects (age > 65)

Robustness 11: Relatives staid in Nursing Home

	<i>Dependent variable: LTCI Demand</i>			
	(1)	(2)	(3)	(4)
Risk Aversion	−0.001 (0.018)			−0.007 (0.018)
Ambiguity Aversion		−0.004 (0.018)		−0.007 (0.019)
Impatience: 2			−0.055 (0.060)	−0.056 (0.060)
Impatience: 3			−0.078 (0.054)	−0.052 (0.056)
Impatience: 4 (Max)			−0.119** (0.056)	−0.064 (0.060)
Bequest Motives (1 = Yes)				0.044 (0.037)
No Family Ties (1 = Yes)				0.046 (0.042)
Care Need (1 = Yes)				0.089** (0.036)
Insurance Performs (1 = Yes)				0.121*** (0.038)
Constant	0.229*** (0.018)	0.229*** (0.018)	0.302*** (0.045)	0.289** (0.137)
Observations	558	558	558	558
R ²	0.00001	0.0001	0.008	0.092
Adjusted R ²	−0.002	−0.002	0.003	0.047
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

Table 3.62: Average Effects (relates in nursing home)

3.9 Appendix Paper III

Differences in Evaluation and Rank-order Stability

This section provides our formal definition of rank-order stability and a proof of a proposition that summarizes the relationship between rank-order stability and identical evaluations of the two application methods.

We start with the formal definition of rank-order stability.

Definition Rank-order-stability: Consider an intertemporal prospect with potential payouts at T different points in time. Denote by $X_{\tilde{t}|x_t=x_{t,k_t}}$ the set of outcomes that may arrive in period $\tilde{t} \leq T-1$ given that the outcome in period $t \leq T-1$ is x_{t,k_t} . An intertemporal prospect is called rank-order stable if for any two outcomes x_{t,j_t} and x_{t,k_t} of any period $t \leq T-1$ with $x_{t,j_t} > x_{t,k_t}$ it holds that $\min(X_{\tilde{t}|x_t=x_{t,j_t}}) \geq \max(X_{\tilde{t}|x_t=x_{t,k_t}})$ for all $\tilde{t} \leq T-1$.

We next state three lemmas that are required to proof the core proposition of this section.

Lemma 1: Denote by $o_j = (o_{j,0}, \dots, o_{j,T-1})$ and $o_k = (o_{k,0}, \dots, o_{k,T-1})$ two outcome streams. Rank-order stability implies that if for any period t the outcome of stream j is larger than the outcome of stream k , $o_{j,t} > o_{k,t}$, then the present-value of stream j is larger than the present value of stream k , $PV(o_j) > PV(o_k)$.

Proof: Under Rank-order stability $o_{j,t} > o_{k,t}$ implies $o_{j,\tilde{t}} \geq o_{k,\tilde{t}}$ for all $\tilde{t} \neq t$ and therefore $PV(o_j) > PV(o_k)$.

□

Lemma 2: Denote by $o_1, o_2, \dots$ the outcome streams and by $PV_1 > \dots > PV_n > 0$ their ordered distinct present values. in addition, denote by $q_1, \dots, q_n$ the associated probabilities. The present-value method transforms the objective probabilities $q_1, \dots, q_n$ into subjective decision weights $\pi_1, \dots, \pi_n$ employing a probability weighting function w^+ . The following calculation rules hold for these subjective decision weights:

- A1: $\pi_1 + \dots + \pi_k = w^+(q_1 + \dots + q_k)$, for all $k \leq n$.
- A2: $\pi_k + \dots + \pi_j = w^+(q_1 + \dots + q_j) - w^+(q_1 + \dots + q_{k-1})$, for all $k > 1$ and $j > k$.

Proof:

$$\begin{aligned}
\pi_1 + \pi_2 + \pi_3 + \dots + \pi_k &= w^+(q_1) + [w^+(q_1 + q_2) - w(q_1)] \\
&+ [w^+(q_1 + q_2 + q_3) - w^+(q_1 + q_2)] + \dots \\
&+ [w^+(q_1 + \dots + q_k) - w^+(q_1 + \dots + q_{k-1})] \\
&= w^+(q_1) - w^+(q_1) + w^+(q_1 + q_2) \\
&- w^+(q_1 + q_2) + \dots + w^+(q_1 + \dots + q_k) \\
&= 0 + \dots + 0 + w^+(q_1 + \dots + q_k) = w^+(q_1 + \dots + q_k)
\end{aligned}$$

$$\begin{aligned}
\pi_k + \pi_{k+1} + \dots + \pi_j &= [w^+(q_1 + \dots + q_k) - w^+(q_1 + \dots + q_{k-1})] \\
&+ [w^+(q_1 + \dots + q_{k+1}) - w^+(q_1 + \dots + q_k)] + \dots \\
&+ [w^+(q_1 + \dots + q_j) - w^+(q_1 + \dots + q_{j-1})] \\
&= -w^+(q_1 + \dots + q_{k-1}) + w^+(q_1 + \dots + q_k) \\
&- w^+(q_1 + \dots + q_k) + \dots + w^+(q_1 + \dots + q_j) \\
&= -w^+(q_1 + \dots + q_{k-1}) + 0 + \dots + 0 + w^+(q_1 + \dots + q_j) \\
&= w^+(q_1 + \dots + q_j) - w^+(q_1 + \dots + q_{k-1})
\end{aligned}$$

□

Lemma 3: Both application methods imply an evaluation of the form

$$\sum_{t=0}^{T-1} \delta(t) \sum_{i=1}^{k_t} \pi_{t,i} v(x_{t,i}).$$

Proof: The evaluation of an intertemporal prospect by the time-separation method is given by

$$V = \sum_{t=0}^{T-1} \delta(t) V_t = \sum_{t=0}^{T-1} \delta(t) \sum_{i=1}^{k_t} \pi_{t,i}^{TS} v(x_{t,i}).$$

The outcome $x_{t,i}$ thus, receives the weight $\pi_{t,i}^{TS}$.

The present value method assigns decision weights to outcome streams. Suppose the outcome stream o_j with present value $\sum_{t=1}^T \delta(t) v(o_{j,t})$ is assigned the decision weight π_j^{PV} . This implies that each outcome of the outcome stream is assigned the weight π_j^{PV} ($\pi_j^{PV} \sum_{t=0}^{T-1} \delta(t) v(o_{j,t}) = \sum_{t=0}^{T-1} \delta(t) \pi_j^{PV} v(o_{j,t})$). Multiple outcome streams may yield the outcome $x_{t,i}$ in period t . The total weight outcome $x_{t,i}$ receives under the present-value

method is, thus, the sum of the weights that the streams containing this outcome receive. Denote this sum by $\pi_{t,i}^{PV}$. If, for instance, the only two streams that contain outcome $x_{t,i}$ are stream o_j and o_k , then $\pi_{t,i}^{PV} = \pi_j^{PV} + \pi_k^{PV}$, with π_j^{PV} and π_k^{PV} denoting the weight assigned to stream o_j and o_k . The evaluation of an intertemporal prospect as suggested by the present-value method can therefore be written as

$$W = \sum_{j=1}^k \pi_j^{PV} V_j = \sum_{t=0}^{T-1} \delta(t) \sum_{i=1}^{k_t} \pi_{t,i}^{PV} v(x_{t,i}).$$

□

Comparing the two evaluations V and W from the proof above, it is obvious that if $\pi_{t,i}^{TS} = \pi_{t,i}^{PV}$ holds for all outcomes $x_{t,i}$, then the two methods yield the same evaluation. The proposition below summarizes the relationship between rank-order stability and identical evaluations.

Proposition 1: If each outcome stream of an intertemporal prospect contains only non-negative or non-positive outcomes and the prospect is rank-order stable, then the evaluations under the two application methods are identical.

Proof: The proof contains two steps.

Step 1: We start the proof by assuming that the prospect only contains non-negative payouts. Denote by $x_{t,1}$ the best outcome of period t and by $p_{t,1}$ its objective probability. The assigned weight under the time-separation method is

$$\pi_{t,1}^{TS} = w^+(p_{t,1}).$$

As displayed in Table 3.63, denote by $o_1 \dots o_{n_{t,1}}$ the $n_{t,1}$ outcome streams that contain the outcome $x_{t,1}$ and by $q_1 \dots q_{n_{t,1}}$ their objective probabilities. Note that $q_1 + \dots + q_{n_{t,1}} = p_{t,1}$. Lemma 1 implies that $o_1, \dots, o_{n_{t,1}}$ are placed in the first $n_{t,1}$ positions if streams are ordered by their present values. Using Lemma 2 A2, the sum of the weights assigned to these streams is therefore equal to

$$w^+(q_1 + \dots + q_{n_{t,1}}) = w^+(p_{t,1}).$$

The outcome $x_{t,1}$ is therefore multiplied by the same factor under both methods.

Denote by $x_{t,2}$ the second best outcome of period t and by $p_{t,2}$ its objective probability.

Stream	Probability	Payout in period t
o_1	q_1	$x_{t,1}$
o_2	q_2	$x_{t,1}$
$\vdots$	$\vdots$	$\vdots$
$o_{n_{t,1}}$	$q_{n_{t,1}}$	$x_{t,1}$
$o_{n_{t,1}+1}$	$q_{n_{t,1}+1}$	$x_{t,2}$
o_2	q_2	$x_{t,2}$
$\vdots$	$\vdots$	$\vdots$
$o_{n_{t,1}+n_{t,2}}$	$q_{n_{t,1}+n_{t,2}}$	$x_{t,2}$
$\vdots$	$\vdots$	$\vdots$

Table 3.63: Intertemporal prospect (for proof)

The assigned weight under the time-separation method is

$$\pi_{t,2}^{TS} = w^+(p_{t,1} + p_{t,2}) - w^+(p_{t,1}).$$

As displayed in Table 3.63 denote by $o_{n_{t,1}+1} \dots o_{n_{t,1}+n_{t,2}}$ the $n_{t,2}$ outcome streams that contain the outcome $x_{t,2}$ and by $q_{n_{t,1}+1} \dots q_{n_{t,1}+n_{t,2}}$ their objective probabilities. Note that $q_{n_{t,1}+1} + \dots + q_{n_{t,1}+n_{t,2}} = p_{t,2}$. Lemma 1 implies that $o_{n_{t,1}+1} \dots o_{n_{t,1}+n_{t,2}}$ are placed in the $n_{t,1} + 1$ to $n_{t,1} + n_{t,2}$ positions if streams are ordered by their present values. Using Lemma 2 A2 the sum of the decision weights assigned to these streams is therefore given by

$$w^+(q_1 + \dots + q_{n_{t,1}+n_{t,2}}) - w^+(q_1 + \dots + q_{n_{t,1}}) = w^+(p_{t,1} + p_{t,2}) - w^+(p_{t,1})$$

The outcome $x_{t,2}$ is therefore multiplied by the same factor under both methods.

The same reasoning as above can also be applied to the other outcomes of period t and also to outcomes of other periods. It therefore holds that $\pi_{t,i}^{PV} = \pi_{t,i}^{TS}$ for all $i \leq k_t$ and $t \leq T - 1$. Because both methods assign the same weights, the evaluations are identical.

Step 2: The same reasoning as in Step 1 can also be applied to prospects that only contain negative payouts. For mixed prospects whose outcome streams either contain only non-negative payouts or non-positive payouts the evaluation can be separated into two parts. The evaluation of the non-negative part yields V^+ under the time-separation method and W^+ under the present-value method. The evaluation of the non-positive part yields V^- and W^- . With the same reasoning as above $V^+ = W^+$ and $V^- = W^-$ holds and, thus, also $V^+ + V^- = W^+ + W^-$.



Lotteries in the Experiment

This section summarizes the lotteries of Set 1 (low-stake gain lotteries) and Set 3 (low-stake mixed lotteries). The loss lotteries (Sets 2 and 5) can be obtained by multiplying all outcomes of the gain lotteries (Sets 1 and 4) by -1 . The high-stake lotteries (Sets 4 to 6) can be obtained by multiplying the low-stake lotteries (Sets 1 to 3) by 20.

Figure 3.19 displays the 8 lotteries of Set 1. All outcomes are in euros. Lotteries 1 to 6 are calibration lotteries, lotteries 7 and 8 test lotteries. The outcome of Lottery 1 at $t = 0$ is either 10 with a low probability or 0 with a high probability. An arrival of the good outcome at $t = 0$ implies the arrival of good outcomes at $t = 1$ (20 with certainty as compared to 10 with certainty) and also at $t = 2$ (50 and 20 equally likely compared to 0 with certainty). Lottery 1, hence, contains two unlikely good outcome streams. Lottery 2 is identical to Lottery 1 except that probabilities at $t = 0$ change. For Lotteries 3 and 4 an arrival of the good outcome at $t = 0$ again implies the arrival of good outcomes at $t = 1$ and also at $t = 2$. Note that the good outcome streams are now likely to arrive. Lottery 5 is a variation of Lottery 1 in which the order of the first two periods and also probabilities at $t = 0$ change. Lottery 6 is a variation of Lottery 5 in which the uncertainty is shifted to the lower (bad) outcome stream. In general, the large number of low-stake outcomes of lotteries 1,2,3,4,5 and 6 ensures that the value function is estimated on a dense grid of small positive values. The large number of distinct outcomes and the variation in probabilities ensures that the probability weighting function is estimated on a dense grid spanning the whole domain.

For the first test lottery, Lottery 7, note that at $t = 0$ and also at $t = 2$ the good outcome (20 at $t = 0$ and 70 at $t = 2$) arrives with probability $1/3$. With a probability weighting function as found in atemporal prospect theory, the time-separation method would assess these probabilities approximately correct (common specifications of the weighting function suggest that a probability of $1/3$ is assessed approximately correct). At $t = 1$, the good outcome 50 arrives with probability $1/6$. With a typical atemporal weighting function, the time-separation method would overweight the good outcome 50 and therefore overestimate the lottery. This is different for the present-value method. The present values of the two best outcome streams (20, 50, 0) and (0, 0, 70) should be similar. The probability that one of these two outcome streams arrives is $1/2$. With a typical atemporal weighting function, the present-value method would underweight these

two streams and therefore underestimate the lottery.

For the second test lottery, Lottery 8, note that at $t = 1$ and also at $t = 2$ the outcome 60 arrives with a probability close or equal to $1/2$. With a typical atemporal weighting function, the time-separation method would underweight the good outcome 60 and, thus, underestimate the lottery. For the present-value method note that the best outcome stream $(10, 50, 60)$ arrives with probability $1/10$. With a typical atemporal weighting function, the present-value method would overweight the best outcome stream and therefore overestimate the lottery.

The lotteries of Set 3 are displayed in Figure 3.20. Lotteries 17 to 22 are calibration lotteries, lotteries 23 and 24 are test lotteries. For the calibration lotteries note that these are replicates of the calibration lotteries of Set 1 (Lotteries 1 to 6 as displayed in Figure 3.19) except that outcomes change. The upper half of each lottery exclusively consists of positive outcomes and the lower half exclusively consists of negative outcomes. The arrival of positive outcomes is unlikely in Lottery 17 and 18. Lottery 19 and 20 are variations of Lottery 17 and 18 in which outcomes are multiplied by -1 and the order of period 2 and 3 changes. Lottery 21 is a variation of Lottery 17 in which the order of the first two periods as well as the probabilities at $t = 0$ change. Lottery 22 is a variation of Lottery 21 in which outcomes are multiplied by -1 . These six calibration lotteries again ensure that the value function is estimated on a dense grid of small values and that the probability weighting function is estimated on a dense grid spanning the whole domain.

For Lottery 23 note that at $t = 1$ the outcome -30 arrives with probability $1/2$; and at $t = 2$ the outcome 60 arrives with probability $1/6$. The time-separation method would underweight the negative outcome -30 and overweight the positive outcome 60, and therefore overestimate the lottery. The situation is different for the present-value method. The lottery contains three positive outcome streams: $(60, -30, 60)$, $(60, 0, 30)$, $(30, 60, 0)$. The present value of these streams should be close to each other. The probability that one of these three streams arrives is $2/3$. The present-value method would therefore underweight these positive streams and, thus, underestimate the lottery.

For Lottery 24, note that at $t = 1$ and also at $t = 2$ the outcome 60 arrives with probability $1/2$. The time-separation method would underweight the positive outcome 60 and therefore underestimate the lottery. For the present-value method note the outcome stream $(60, 60, 60)$ arrives with probability $1/6$. The present-value method therefore

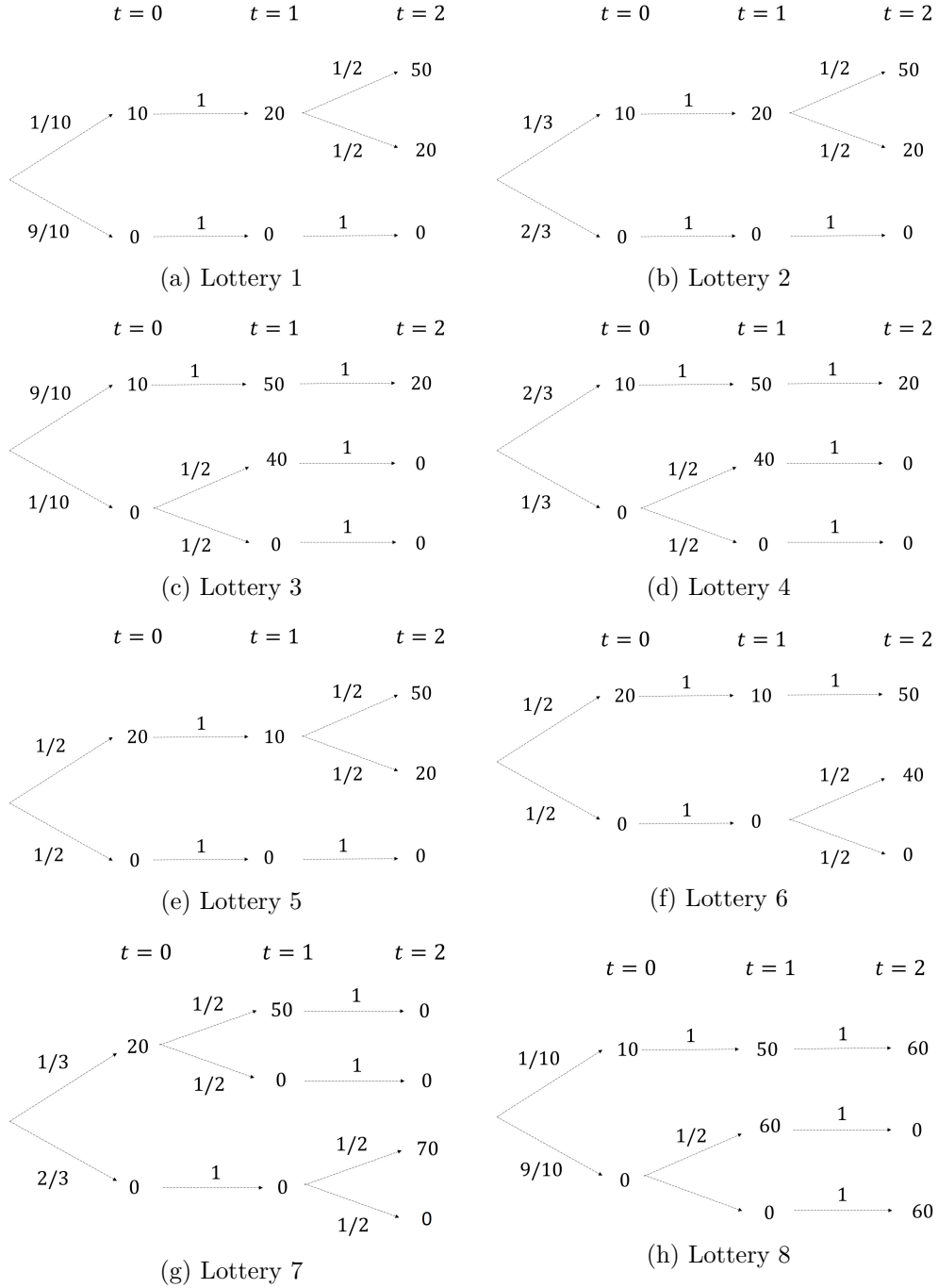


Figure 3.19: Lottery Set 1 (low-stake gain lotteries)

overweights this stream and, hence, overestimates the lottery.

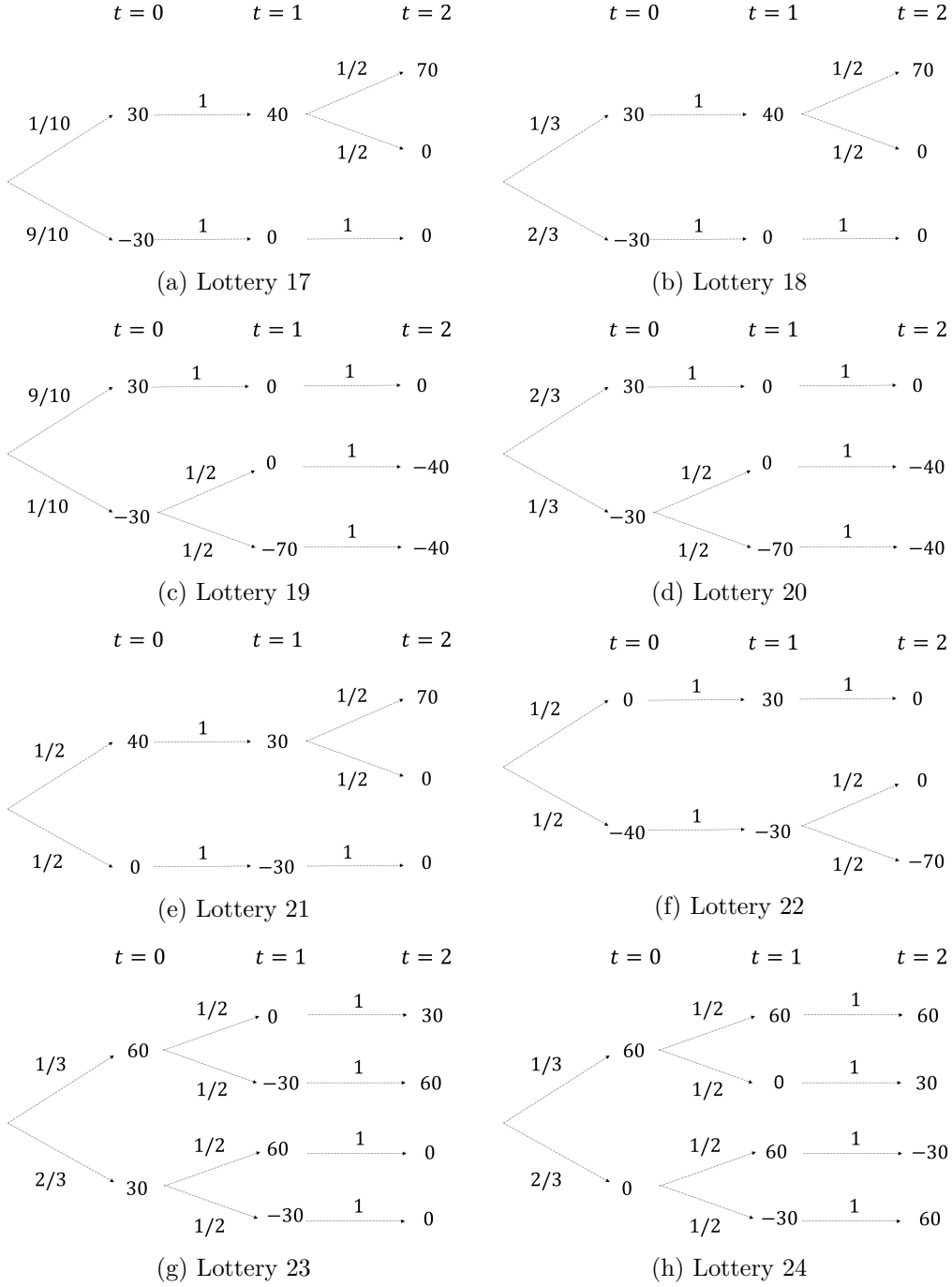


Figure 3.20: Lottery Set 3 (low-stake mixed lotteries)

In general, the test lotteries are set up so that the evaluations under the two methods give (sizably) different results. In order to assure a fair comparison between the two methods we choose the test lotteries such that the degree to which one method over- and the other method underestimates the lottery are similar (assuming typical atemporal calibrations). Table 3.64 summarizes these features of our test lotteries.

	No weighting	Time-separation		Present-value	
	CE	CE	Rel. deviation	CE	Rel. deviation
	(1)	(2)	(3)	(4)	(5)
Lottery 7	10.6	12	0.13	9.2	-0.13
Lottery 8	19.3	17	-0.09	20.8	0.08
Lottery 15	211.2	240.4	0.14	184.3	-0.13
Lottery 16	386.1	340.2	-0.1	416.6	0.08
Lottery 23	-10.6	-12	-0.13	-9.2	0.13
Lottery 24	-19.3	-17	0.09	-20.8	-0.08
Lottery 31	-211.2	-240.4	-0.14	-184.3	0.13
Lottery 32	-386.1	-340.2	0.12	-416.6	-0.08
Lottery 39	11	13.3	0.21	8.6	-0.22
Lottery 40	9.8	7.1	-0.28	12.4	0.27
Lottery 47	220.3	265.4	0.2	171.8	-0.22
Lottery 48	195.9	141.1	-0.28	248.8	0.27

Notes: To calculate the certainty equivalents we use the parametric specifications suggested by Tversky and Kahneman (1992) i.e., $v(x) = \mathbb{1}(x \geq 0)x^{0.88} - \mathbb{1}(x < 0)2.25(-x)^{0.88}$, and $w^+(p) = w^-(p) = \frac{p^{0.69}}{(p^{0.69} + (1-p)^{0.69})^{1/0.69}}$ (without time discounting).

Table 3.64: Overview test lotteries (12 Lotteries)

Experimental Instructions and Comprehension Test Question

In Section 3.9, we reproduce the complete experimental instructions that subjects receive before the experiment. Section 3.9 contains the comprehension test questions that participants have to answer correctly before starting with the decision tasks. Section 3.9 contains the information that participants receive during the experiment before starting each of the six blocks of decision tasks (that appear in random order). Section 3.9 contains the brief post-experimental questionnaire. All texts are in English translation.

We provide the information for both treatments jointly. If nothing is indicated, texts and figures are shown in both treatments. Where there is a difference, this is indicated by highlighted brackets. The first part in the brackets applies to the hypothetical treatment T1, the latter part to the incentivized treatment T2. For instance, [example text / different example text] signifies that participants in T1 see “example text”, while participants in T2 see “different example text”. [NO TEXT / example text] signifies that participants in T1 do not see any text for this part, while participants in T2 see “example text”.

Experimental Instructions

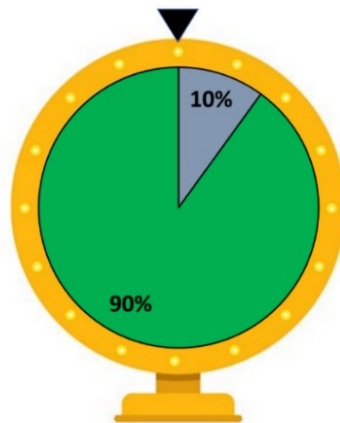
The aim of this research is to better understand how people make decisions. The research is carried out by researchers from the University of St. Gallen in Switzerland.

The experiment consists of 6 parts. In each part you will complete eight decision tasks, thus 48 decision tasks in total. Please read the following explanation carefully.

■ The decisions you make in this questionnaire do not affect your payments for this questionnaire. Please make your decisions as if they involved real monetary gains or losses. / In addition to the regular payment for completing this questionnaire, there will be an additional payment depending on your decisions. This will be explained later. Not all decisions will affect your earnings, but please make all decisions as if they involved real monetary gains or losses. ■

General Instructions

Probabilities (expressed in percentages) play an important role in this research. We will use a wheel of fortune to display probabilities.



The probability that the black indicator (on the top of the wheel) points at a grey part after spinning the wheel is equal to 10%, because 1/10 (one tenth) of the wheel is grey. The probability that the black indicator points at a green part after spinning the wheel is thus equal to 90%, because 9/10 (nine tenths) of the wheel are green.

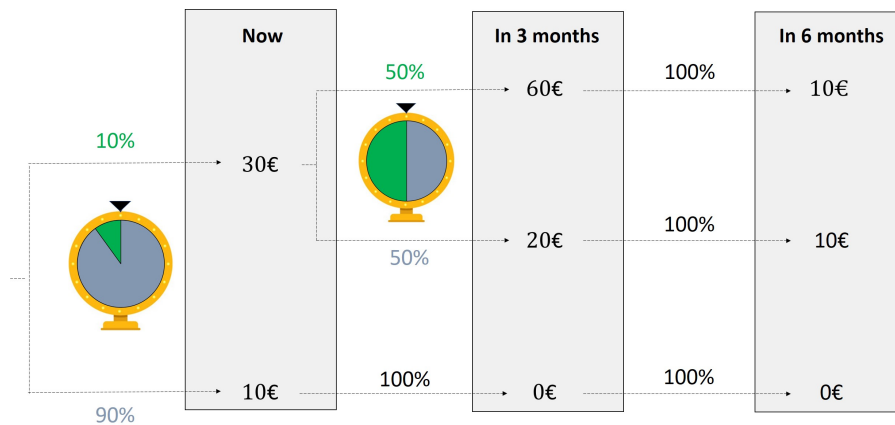
Time also plays an important role in this research. As displayed by the grey areas in the table below, payments can be made "now", "in 3 months" or "in 6 months".

Each decision task will involve a *safe option* and a *risky option*. A risky option yields monetary payouts with certain probabilities. Each risky option may have payouts now, in 3 months and in 6 months. As will be explained below, the payout in 3 months depends

Now (Time of payment for participation)			In 3 months			In 6 months
First payout from your choice			Second payout from your choice			Third payout from your choice

on the payout now. The payout in 6 months depends on the payout in 3 months.

We explain how the risky option works with the example below. In the chart, you see two wheels of fortune that show illustrate the probabilities.



The payout now is either 30 euro or 10 euro. The probability that 30 euro are paid is 10% and the probability that 10 euro are paid is 90%, as the arrows in the first block (Now) show.

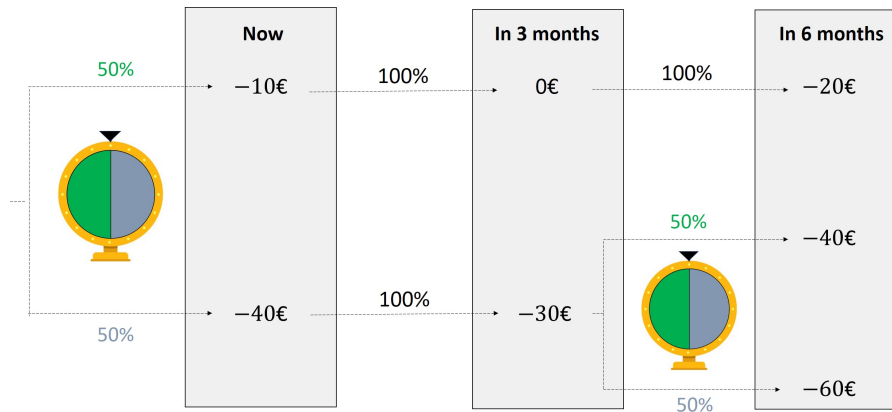
In addition to the payout now, the risky option yields a payout in 3 months and a payout in 6 months. The additional payout in 3 months depends on the payout now and is 60 euro, 20 euro, or 0 euro.

- If the payout now is 30 euro, then the payout in 3 months is 60 euro with probability 50% and 20 euro with probability 50%, as indicated by the arrows in the second block (in 3 months).
- If the payout now is 10 euro, then the payout in 3 months is 0 euro, as the arrow between the 10 euro in the first block (now) and the 0 euro in the second block (in 3 months) shows.

The additional payout in 6 months is either 10 euro or 0 euro depending on the payout in 3 months.

- If the payout in 3 months is 20 euro or 60 euro, then the payout in 6 months is 10 euro with certainty.
- If the payout in 3 months is 0 euro, then the payout in 6 months is also 0 euro.

Here is another example. Note that there are only negative payouts in this example.

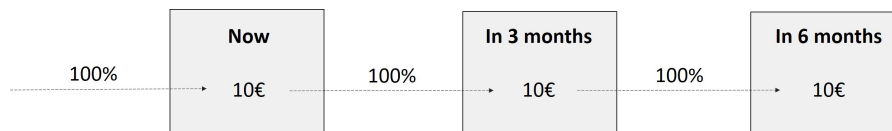


For negative payouts you should imagine that you have to pay money to the researcher, thus that you lose money. In this example, in the block 'now', is the probability 50% that the payout is -10 euro and the probability is 50% that the payout is -40 euro. The additional payout in 3 months is either 0 euro or -30 euro and depends on the payout now. If, for example, the payout now is -10 euro, then the payout in 3 months is 0 euro. The additional payout in 6 months is then -20 euro, -40 euro, or -60 euro and depends on the payout in the second block (in 3 months). If the payout there is -30 euro, then the probability is 50% that the payout in 6 months is -40 euro and 50% that the payout is -60 euro.

The two examples that you saw gave only positive or only negative payouts. In the research, there is also a third type of risky option, which contains a mix of positive and negative payouts.

Decisions

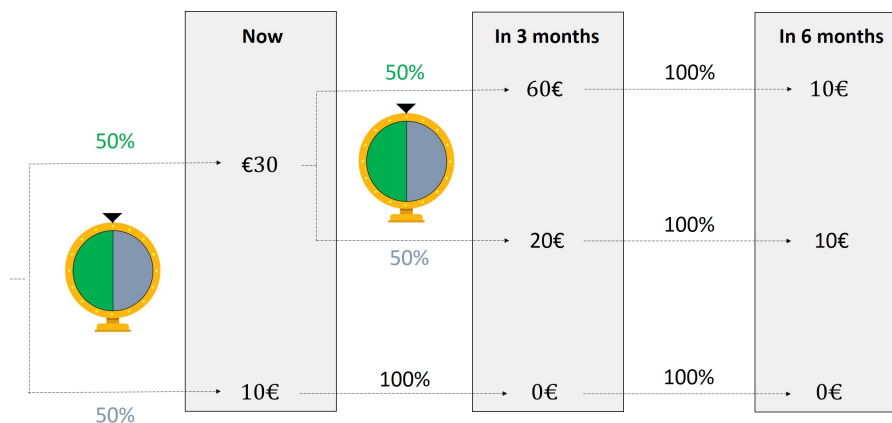
In each decision task there is one risky option. You can choose between the risky option and a safe option. Both options (risky or safe) yield payouts at three different points in time (now, in 3 months, and in 6 months). In contrast to the payouts of the risky option, the payouts of the safe option are **certain** and they are **always the same**. As displayed in the figure below, the safe option can, for example, yield a certain payout sequence of 10 euro now, 10 euro in three months, and 10 euro in six months.



Each decision screen contains three elements. The first element is a chart that displays the payout structure of the risky option. The second element is a chart that displays the payouts of the safe option. The third element is a "slider" that you can position in order to indicate for which amounts paid in the safe option you would rather have the risky option than the safe option. An example of the three elements together is displayed below.

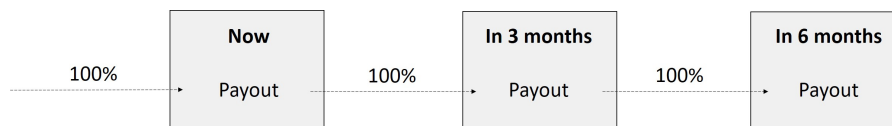
Element 1

Consider the risky option for this decision task.



Element 2

The alternative to the risky option is a safe option that yields three certain and identical payouts:



Element 3

Below you can see the slider that you can move.

I choose the risky option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:	I choose the safe option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:
3€ and 3€	4€ and 34€

3€

34€

You can move the slider to the left and to the right to indicate your choice. There are no right or wrong choices: the position of the slider indicates what you prefer and preferences may be different for different people.

Example: Assume that you prefer the risky option as long as the certain amount of the safe option that you would receive three times (once now, once in 3 months, once in 6 months) is 11 euro or less. However, if the certain amount of the safe option that you would receive three times is 12 euro or more (thus in total 36 euro or more), you prefer the safe option. Then you have to position the slider as displayed below.

I choose the risky option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:	I choose the safe option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:
3€ and 11€	12€ and 34€

3€

34€

In this example, the risky option only contains **positive** payouts. But you will also see risky options that only contain **negative** payouts (you do not receive money, but you have to pay) and risky options that contain a mix of positive and negative payouts

Imagine: You consider a risky option with only negative payouts the lesser evil when the amount in the safe option that you would lose three times (once now, once in 3 months, once in 6 months) is 22 euro or more (thus in total 66 euro or more). You, however, perceive the risky option as the greater evil when the amount that you would lose three times in the safe option is 21 euro or less (which means that you would lose in total at most 63 euro). Then you have to position the slider as shown here:

Thus, each decision task thus has two options to choose from:

- a risky option where the payouts at three different points in time (now, in 3 months, and in 6 months) are uncertain.

I choose the risky option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:	I choose the safe option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:
-30€ and -22€	-21€ and 0€

-30€
0€



- a safe option that yields three payouts (now, in 3 months and in 6 months) that are the same.

You are asked to position a slider to indicate for which amounts that you receive three times in the safe option, you would prefer the risky option over the safe option.

I NO TEXT / **Payments**

You receive a compensation for completing this questionnaire. But you can also earn an extra payment, depending on your choices and on luck. This extra payment is calculated as follows. The research consists of six parts. In each part, there are eight decision tasks, thus 48 in total. In two of the six parts, there are risky options that only contain positive payouts. The eight risky options in one of these two parts yield small to medium payouts, whereas the eight risky options in the other part yield medium to high payouts. One of these 16 decision tasks will be randomly selected for payment at the end of the questionnaire. There is a 1% chance that the selected decision task is from the part with medium to large payouts, and there is a 99% chance that the selected decision task is from the part with small to medium payouts. The decisions you make in the other four parts cannot be selected for payment.

In the example below, we describe how the payment for the randomly selected decision task is calculated. Assume that you positioned the slider in the selected decision task as displayed below:

I choose the risky option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:	I choose the safe option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:
3€ and 11€	12€ and 34€

3€
34€



The computer then randomly selects an amount between the lower and upper limits

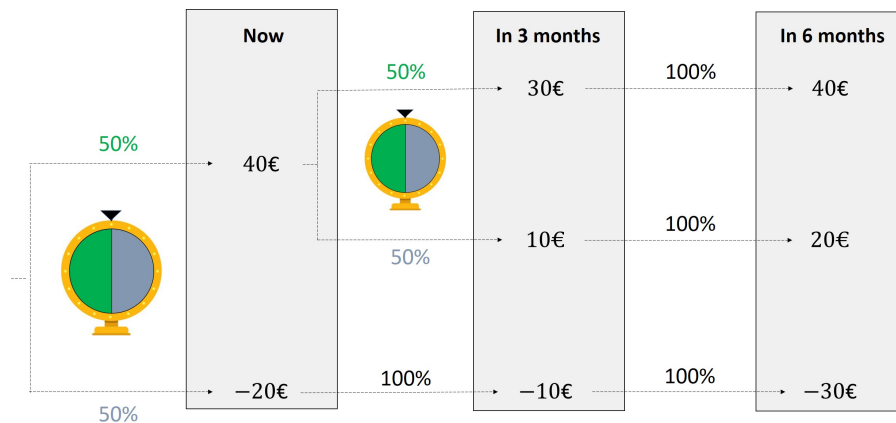
of the slider, in this example thus between 3 euro and 33 euro. All amounts on the slider are equally likely to be selected. You will then receive the option that you chose for the randomly selected amount. In this example:

- If the randomly selected amount is 12 euro or more, the slider shows that you prefer receiving this amount three times (now, in 3 months, in 6 months) over the three uncertain payouts of the risky option. If, for example, the randomly selected amount is 13 euro, you receive 13 euro now, 13 euro in 3 months, and 13 euro in 6 months.
- If the randomly selected amount is 11 euro less, the slider shows that you prefer the risky option. Your payment will then be determined through the risky option. The computer will then randomly determine the outcomes, and you will be told the results at the end of the questionnaire. Also here, the payouts will take place now, in 3 months, and in 6 months. 

Before the first part of the research starts, we would like to ask you a few test questions to make sure that you fully understand the instructions.

Please click "Next" to proceed to the questions.

Comprehension Test Questions



Question 1: Consider the risky option above and indicate for each statement whether it is true or false.

- The payout now is either 40 euro with probability 50% or -20 euro with probability 50%.
- If the payout now is -20 euro (you lose 20 euro), then the payout in 3 months is -10 euro (you lose 10 euro) with certainty, and the payout in 6 months is -30 euro (you lose 30 euro) with certainty.



Question 2: Consider the risky option above and indicate for each statement whether it is true or false.

- The payout now is 0 euro with probability 10%. If the payout now is 0 euro, then the payout in 3 months is 10 euro. If the payout is 10 euro in three months, then the payout in 6 months is 20 euro with probability 50%. The probability that the payouts are 0 euro now, 10 euro in 3 months, and 20 euro in six months is, thus, 5%, because 50% of 10% is 5%.
- The payout in three months can only be 30 euro if the payout now is 40 euro. The payout now is 40 euro with probability 90%. After a payout of 40 euro now, the payout in 3 months is 30 euro with probability 50%. The payout in three months is, thus, 30 euro with probability 45%, because 50% of 90% is 45%.



I choose the risky option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:	I choose the safe option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:
3€ and 22€	23€ and 34€

3€  34€

Question 3: Consider the slider displayed above and indicate whether the following statement is true or false.

- The position of the slider shows that if you are offered certain payouts of three times 20 euro (20 euro now, 20 euro in 3 months and 20 euro in 6 months), then you would reject these certain payouts and instead prefer the risky option.

/

Part of your payment for the decision tasks depends on luck and your decisions in two of the six parts of the questionnaire. For this, only one decision task will be randomly selected. Assume that you positioned the slider in the randomly selected decision task as shown here:

I choose the risky option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:	I choose the safe option if the payout amount of the safe option that I receive three times (now, in 3 months and in 6 months) lies between:
3€ and 22€	23€ and 34€

3€  34€

The computer randomly selects an amount between 3 euro and 33 euro. All amounts are equally likely to be selected. Assume that the randomly selected amount is 20 euro.

Question 3: Please indicate whether the following statement is true or false.

- The position of the slider shows that if you are offered certain payouts of three times 20 euro (20 euro now, 20 euro in 3 months and 20 euro in 6 months), then you would reject these certain payouts and instead choose the risky option. The risky option will then determine the payments. The payouts take place now, in 3 months, and in 6 months. The money will be thus be paid at three different points in time.



Information Before Each Block of Decision Tasks During the Experiment

Information before starting the decision tasks of block 1:

In the eight decisions tasks of this part you will see risky options that yield small-to-medium positive payouts (gains).

[NO TEXT / As explained earlier, only one decision task will be randomly selected for payment at the end of the questionnaire. There is a 99% chance that one of the eight decision tasks from this part will be selected for payment.

[

Please click on the “Next” button to proceed to the first decision task of this part.

Information before starting the decision tasks of block 2:

In the eight decisions tasks of this part you will see risky options that yield medium-to-large positive payouts (gains).

[NO TEXT / As explained earlier, only one decision task will be randomly selected for payment at the end of the questionnaire. There is a 1% chance that one of the eight decision tasks from this part will be selected for payment.

[

Please click on the “Next” button to proceed to the first decision task of this part.

Information before starting the decision tasks of block 3:

In the eight decisions tasks of this part you will see risky options that yield small-to-medium negative payouts (losses).

Please click on the “Next” button to proceed to the first decision task of this part.

Information before starting the decision tasks of block 4:

In the eight decisions tasks of this part you will see risky options that yield medium-to-large negative payouts (losses).

Please click on the “Next” button to proceed to the first decision task of this part.

Information before starting the decision tasks of block 5:

In the eight decisions tasks of this part you will see risky options that yield small-to-medium positive payouts (gains) but also small-to-medium negative payouts (losses).

Please click on the “Next” button to proceed to the first decision task of this part.

Information before starting the decision tasks of block 6:

In the eight decisions tasks of this part you will see risky options that yield medium-to-large positive payouts (gains) but also medium-to-large negative payouts (losses).

Please click on the “Next” button to proceed to the first decision task of this part.

Post-experimental Questionnaire

You have now completed all six parts with decision tasks. There are only a few questions remaining.

During the decision tasks we asked you to position a slider. Was it clear for you what the position of the slider meant?

- Very clear
- Rather clear
- Unclear

During the decision tasks we asked you to evaluate risky options with uncertain payouts at three different points in time. How complicated were these decision tasks?

- Okay
- Complicated
- Too complicated

Please honestly report your attention during the questionnaire.

- I paid attention in all six parts.
- I paid attention in most of the six parts.
- I only paid attention in a few parts or not at all.

When making your decisions, did you take into consideration that the payouts of the risky option arrive at three different points in time?

- Always
- Sometimes
- Never

Additional Data Analysis

Exclusion Criteria

Table 3.65 summarizes subjects' responses in the post-game survey. The relative share of subjects that gave a specific answer is added in parentheses. Subjects are excluded if they answer at least one of these questions with the 'worst' answer possibility. Table 3.66 summarizes the distribution of 'worst' answers. Note that the same subject may give the 'worst' answer to several questions.

The second exclusion criteria is the median decision time. Table 3.67 provides an overview of the median decision times among i) the subjects that started the experiment ($n = 391$), ii) the subjects that were excluded due to their responses in the post-game survey or because they did not finish the experiment ($n = 205$), iii) the subjects that finished the experiment and were not excluded due to their responses in the post-game survey ($n = 186$).

Q1: Was it clear what the position of the slider meant?			
Answer	Very clear	Rather clear	Unclear
n	106 (28%)	153 (40%)	119 (31%)
Q2: How complex were the decision tasks?			
Answer	Okay	Complicated	Too complicated
n	101 (26%)	159 (42%)	118 (31%)
Q3: In how many parts did you pay attention?			
Answer	All parts	Most parts	Few parts
n	103 (27%)	130 (34%)	145 (38%)

Table 3.65: Summary post-game survey responses

Worst response to	n
Only Q1	17
Only Q2	17
Only Q3	33
Q1 and Q2	13
Q1 and Q3	24
Q2 and Q3	23
Q1 and Q2 and Q3	65

Table 3.66: Exclusion by post-game survey

Median time per decision (in seconds)	[0-5)	[5 - 15)	[15 - 30)	[30 - 45)	> 45
Full sample	133	125	66	33	34
Excluded due to survey	95	77	25	7	1
Not excluded due to survey	38	48	41	26	33

Table 3.67: Overview median decision time

Demographic Variables of Participants

Table 3.68 presents summary statistics of main demographic variables of our sample and of the representative subject pool. Column (1) displays the statistics of our main sample ($n = 100$). Columns (2) and (3) display summary statistics of the excluded subjects ($n = 291$) and of the entire representative subject pool from which the participants of our experiment were drawn ($n = 8976$). Comparing these samples we only observe statistically significant differences for i) the share of participants with academic education and ii) the share of participants with an income larger than 4500 Euros (which is only marginally significant when comparing our final sample to the original pool).

	Final (1)	Excluded (2)	Pool (3)	t-tests	
				(1) vs. (2)	(1) vs. (3)
Sex (1 = Female)	0.48	0.50	0.51		
Age ≤ 24	0.11	0.08	0.09		
Age 25 – 44	0.28	0.26	0.31		
Age 45 – 64	0.30	0.37	0.33		
Age ≥ 65	0.31	0.30	0.27		
Income ≤ 1500	0.28	0.30	0.30		
Income 1501 – 3000	0.27	0.30	0.33		
Income 3001 – 4500	0.26	0.20	0.19		
Income > 4500	0.16	0.11	0.10		*
Primary education	0.05	0.09	0.06		
Secondary education	0.23	0.30	0.30		
Vocational education	0.51	0.51	0.50		
Academic education	0.21	0.11	0.14	**	*

Notes: * and ** indicate significant differences of t-tests at the 10%-level and 5%-level.

Table 3.68: Demographic variables of participants

Prediction Error by-Lottery

Table 3.69 displays the mean absolute prediction error of the time-separation (TS) and present-value method (PV). The column names refer to the 12 test lotteries and the

row names refer to the model combinations as in Table 3.4. The payout ranges of the lotteries are displayed in parentheses. Table 3.70 shows the weighted mean-squared errors of the time-separation and present-value methods per lottery.

Comb.	Meth.	Low-stake lotteries						High-stake lotteries					
		L7 (23)	L8 (20)	L15 (23)	L16 (20)	L23 (30)	L24 (50)	L31 (467)	L32 (400)	L39 (467)	L40 (400)	L47 (600)	L48 (1000)
C1	TS	6.0	8.1	7.3	5.6	7.9	16.7	144.1	148.6	146	124.9	180	319.9
	PV	5.2	5.6	6.1	5.6	7.2	14.6	108.5	118	114.4	115	150.7	276.8
C2	TS	6.0	8.1	7.3	5.6	8.2	16.3	144.0	148.1	145.9	125.4	188.1	312.3
	PV	5.2	5.6	6.1	5.6	7.0	14.5	108.5	117.7	114.4	114.0	150.6	275.3
C3	TS	6.1	8.1	7.7	5.5	7.5	18.0	149.3	148.6	155.9	123.1	170.4	347.1
	PV	5.7	6.5	6.1	5.3	7.5	14.6	104.5	124.3	116.0	110.3	153.9	279.1
C4	TS	6.2	8.1	7.6	5.5	8.0	17.7	150.6	148.6	153.9	125.4	183.8	339.3
	PV	5.7	7.1	6.1	5.4	7.1	14.6	104.5	132.2	116.0	113.2	150.6	277.6
C5	TS	6.2	8.0	7.9	5.6	7.6	17.6	152.2	148.1	162.4	117.9	174.0	339.2
	PV	5.5	6.2	6.0	5.3	7.4	14.6	104.8	121.2	114.3	109.9	152.1	278.6
C6	TS	6.1	8.1	7.6	5.6	7.6	17.8	149.4	148.6	152.8	123.2	172.6	341.5
	PV	5.5	6.3	6.0	5.3	7.5	14.7	104.7	122.4	115.2	110.1	153.1	279.9
C7	TS	5.3	8.1	6.4	5.6	7.1	17.7	122.4	146.6	128.3	125.4	161	340.7
	PV	5.6	6.2	6.1	5.3	7.5	15.1	104.6	120.8	114.2	109.9	153.4	288.9
C8	TS	5.3	8.1	6.4	5.6	7.1	17.7	122.4	148.6	128.3	125.4	161.0	340.7
	PV	5.6	6.2	6.1	5.3	7.5	15.1	104.6	120.8	114.2	109.9	153.4	288.9
C9	TS	5.3	8.1	6.4	5.6	7.1	17.7	122.4	144.3	128.3	125.4	161.0	340.7
	PV	5.6	6.2	6.1	5.3	7.5	15.1	104.6	120.8	114.2	109.9	153.4	288.9
C10	TS	6.4	7.6	7.8	5.5	7.9	16.7	128.6	141.2	131.4	125.4	158.3	362.6
	PV	5.3	5.7	6.0	5.3	7.2	14.6	104.5	127.5	116.3	111.3	158.6	290.4
C11	TS	6.4	7.9	7.9	5.6	8.8	16.1	129.5	148.6	134.9	121.4	170.1	348.4
	PV	5.3	6.0	6.0	5.3	6.9	14.5	104.5	135.2	115.6	114.0	150.7	286.9
C12	TS	6.6	7.4	8.0	5.4	8.1	16.5	132.7	148.6	136.0	123.4	161.4	355.4
	PV	5.2	5.7	6.0	5.3	7.1	14.5	104.5	128.4	115.7	111.6	156.8	288.1

Notes: The mean absolute prediction error of Lottery j is calculated as $\text{mean}(|CE_{i,j} - \widehat{ce}_j|)$, with $CE_{i,j}$ denoting the certainty equivalent subject j reported for Lottery j and $\widehat{ce}_j$ denoting the predicted certainty equivalent resulting from the parameters estimated on the calibration set. Payout ranges are shown in parentheses below the lottery number.

Table 3.69: Mean absolute prediction error (by lottery)

Comb.	Meth.	Low-stake lotteries							High-stake lotteries				
		L7	L8	L15	L16	L23	L24	L31	L32	L39	L40	L47	L48
C1	TS	0.10	0.27	0.15	0.18	0.11	0.19	0.13	0.25	0.15	0.21	0.14	0.17
	PV	0.08	0.11	0.10	0.10	0.09	0.13	0.08	0.11	0.09	0.11	0.09	0.12
C2	TS	0.10	0.27	0.15	0.18	0.12	0.18	0.13	0.25	0.15	0.21	0.15	0.17
	PV	0.08	0.11	0.10	0.10	0.08	0.12	0.08	0.12	0.09	0.11	0.09	0.12
C3	TS	0.10	0.27	0.16	0.18	0.10	0.22	0.14	0.25	0.16	0.20	0.13	0.20
	PV	0.09	0.17	0.10	0.12	0.10	0.13	0.08	0.16	0.09	0.13	0.09	0.12
C4	TS	0.10	0.27	0.16	0.18	0.12	0.21	0.14	0.25	0.16	0.21	0.15	0.19
	PV	0.09	0.20	0.10	0.15	0.08	0.13	0.08	0.20	0.09	0.16	0.09	0.12
C5	TS	0.11	0.27	0.17	0.18	0.11	0.21	0.15	0.25	0.18	0.18	0.13	0.19
	PV	0.09	0.15	0.10	0.11	0.09	0.13	0.08	0.15	0.09	0.12	0.09	0.12
C6	TS	0.10	0.27	0.16	0.18	0.10	0.21	0.14	0.25	0.16	0.20	0.13	0.20
	PV	0.09	0.16	0.10	0.12	0.09	0.13	0.08	0.15	0.09	0.13	0.09	0.12
C7	TS	0.08	0.27	0.11	0.18	0.09	0.21	0.10	0.25	0.12	0.21	0.11	0.20
	PV	0.09	0.15	0.10	0.12	0.09	0.15	0.08	0.15	0.09	0.12	0.09	0.14
C8	TS	0.08	0.27	0.11	0.18	0.09	0.21	0.10	0.25	0.12	0.21	0.11	0.20
	PV	0.09	0.15	0.10	0.12	0.09	0.15	0.08	0.15	0.09	0.12	0.09	0.14
C9	TS	0.11	0.24	0.17	0.17	0.12	0.19	0.11	0.25	0.12	0.21	0.11	0.22
	PV	0.08	0.12	0.10	0.10	0.09	0.13	0.08	0.18	0.09	0.14	0.10	0.14
C10	TS	0.11	0.26	0.17	0.18	0.14	0.18	0.11	0.25	0.13	0.21	0.13	0.20
	PV	0.08	0.14	0.10	0.11	0.08	0.12	0.08	0.21	0.09	0.16	0.09	0.13
C11	TS	0.12	0.23	0.18	0.16	0.12	0.18	0.11	0.25	0.13	0.21	0.11	0.21
	PV	0.08	0.12	0.10	0.10	0.09	0.12	0.08	0.18	0.09	0.15	0.10	0.14
C12	TS	0.12	0.23	0.18	0.16	0.12	0.18	0.11	0.25	0.13	0.21	0.11	0.21
	PV	0.08	0.13	0.10	0.10	0.08	0.12	0.08	0.18	0.09	0.15	0.09	0.13

Notes: This table contains the (weighted) MSE for each test lottery and each function combination separately.

Table 3.70: MSE (by lottery)

Prediction Error by-Participant

Figure 3.21 shows the distribution of the MSE difference ($MSE_{TS} - MSE_{PV}$) on the participant level. The MSE difference is calculated for each participant using the aggregate level parameter estimates displayed in Table 3.71 below (these are the parameter estimates on the calibration set). The labels C1 to C12 refer to the combinations as in Table 3.4. For each of the 12 combinations the MSE difference is (sizable) larger than 0 for a majority of the participants.

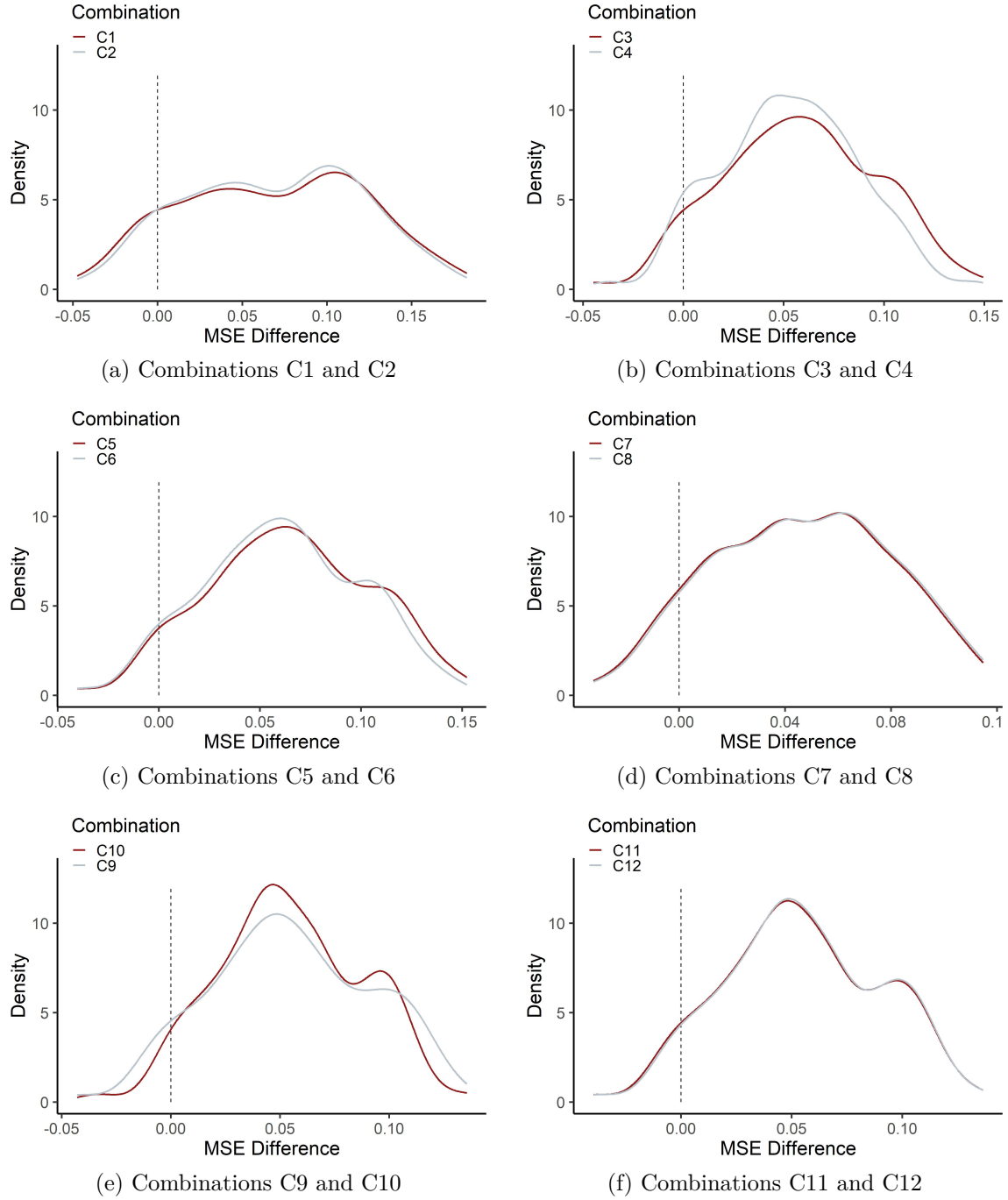


Figure 3.21: Densities of by-participant MSE differences ($MSE_{TS} - MSE_{PV}$)

Notes: This figure shows the empirical density functions of differences in MSE per participant ($MSE_{TS} - MSE_{PV}$). Always two function combinations are shown in one panel, only differing by the type of time discounting (exponential or quasi hyperbolic).

Parameter Estimates on the Calibration Set

Table 3.71 shows the parameters estimated on the calibration set (with bootstrapped standard errors in parentheses). These estimates are identical for the time-separation and the present-value method. The labels C1 to C12 refer to the combinations as in Table 3.4. Combinations C1 to C6, thus, summarize the parameter estimates for the model combinations that employ power utilities as basic utility functions. Combinations C7 to C12 summarize the parameters for the model combinations that employ exponential utilities as basic utility functions. The coefficients for exponential utility (α and β) in C7 to C12 are multiplied by a factor of 1000.

Combination	Value		Weighting				Discounting		
	α	β	λ	$\gamma+$	$\gamma-$	$\nu+$	$\nu-$	r	k
C1	1.172		1.176	0.530	0.550			0	
	(0.072)		(0.275)	(0.041)	(0.061)			(0)	
C2	1.182		1.089	0.536	0.557			0	0.943
	(0.081)		(0.295)	(0.04)	(0.061)			(0)	(0.069)
C3	0.817		1.062	0.471	0.481	0.729	0.701	0.001	
	(0.126)		(0.254)	(0.07)	(0.092)	(0.123)	(0.151)	(0.012)	
C4	0.801		1.072	0.488	0.508	0.681	0.657	0	0.845
	(0.123)		(0.206)	(0.072)	(0.094)	(0.119)	(0.145)	(0.003)	(0.063)
C5	0.896		1.116	0.432	0.443	1.052	1.115	0	
	(0.061)		(0.244)	(0.06)	(0.072)	(0.112)	(0.168)	(0.006)	
C6	0.891		1.142	0.425	0.437	1.050	1.101	0	0.990
	(0.062)		(0.243)	(0.06)	(0.072)	(0.108)	(0.167)	(0.005)	(0.037)
C7	-0.016	-0.120	1.137	0.617	0.636			0	
	(0.150)	(0.1)	(0.210)	(0.033)	(0.042)			(0)	
C8	-0.016	-0.120	1.137	0.617	0.636			0	1
	(0.149)	(0.096)	(0.212)	(0.032)	(0.042)			(0)	(0)
C9	0.418	0.402	1.136	0.455	0.476	0.870	0.850	0.002	
	(0.126)	(0.115)	(0.219)	(0.062)	(0.081)	(0.047)	(0.04)	(0.014)	
C10	0.406	0.382	1.09	0.474	0.494	0.841	0.812	0	0.843
	(0.124)	(0.117)	(0.184)	(0.062)	(0.082)	(0.052)	(0.046)	(0.003)	(0.060)
C11	0.40	0.390	1.123	0.441	0.456	0.961	1.013	0.004	
	(0.128)	(0.119)	(0.217)	(0.06)	(0.073)	(0.070)	(0.076)	(0.010)	
C12	0.392	0.376	1.105	0.443	0.456	0.964	1.016	0	0.979
	(0.131)	(0.119)	(0.226)	(0.061)	(0.073)	(0.074)	(0.08)	(0.005)	(0.037)

Notes: This table shows the parameter estimates on the calibration set, for four selected function combinations. These estimates are identical for time-separation and present-value methods.

Table 3.71: Overview parameter estimates on calibration set (36 lotteries)

Parameter Estimates for the Present-value Method (All Lotteries)

Table 3.72 shows the parameter estimates (with standard errors in parentheses) for the present-value method. The labels C1 to C12 refer to the combinations as in Table 3.4. Combinations C1 to C6, thus, summarize the parameter estimates for the model combinations that employ power utilities as basic utility functions. Combinations C7 to C12 summarize the parameters for the model combinations that employ exponential utilities as basic utility functions. The coefficients for exponential utility (α and β) are multiplied by a factor of 1000.

Combination	α	Value β	λ	$\gamma+$	Weighting $\gamma-$	$\nu+$	$\nu-$	Discounting r	k
C1	1.195 (0.068)		1.069 (0.096)	0.535 (0.045)	0.551 (0.06)			0.117 (0.036)	
C2	1.172 (0.061)		1.065 (0.121)	0.547 (0.043)	0.565 (0.057)			0.016 (0.025)	0.863 (0.043)
C3	1.092 (0.04)		1.010 (0.150)	0.406 (0.067)	0.427 (0.082)	0.992 (0.065)	0.988 (0.057)	0.076 (0.032)	
C4	1.080 (0.032)		1.104 (0.182)	0.425 (0.068)	0.453 (0.08)	0.976 (0.059)	0.975 (0.054)	0 (0.003)	0.855 (0.037)
C5	1.091 (0.035)		1.037 (0.127)	0.426 (0.066)	0.448 (0.073)	0.766 (0.074)	0.786 (0.071)	0.070 (0.028)	
C6	1.085 (0.03)		1.101 (0.163)	0.423 (0.07)	0.451 (0.073)	0.786 (0.073)	0.796 (0.068)	0.0012 (0.016)	0.884 (0.045)
C7	-0.115 (0.066)	-0.116 (0.065)	0.960 (0.095)	0.622 (0.035)	0.639 (0.042)			0 (0)	
C8	-0.122 (0.065)	-0.112 (0.065)	0.919 (0.096)	0.624 (0.036)	0.638 (0.043)			0 (0)	1 (0)
C9	0.078 (0.049)	0.200 (0.060)	0.925 (0.113)	0.452 (0.07)	0.446 (0.086)	0.897 (0.05)	0.861 (0.036)	0 (0.013)	
C10	0.07 (0.05)	0.166 (0.061)	1 (0.116)	0.442 (0.069)	0.450 (0.086)	0.879 (0.049)	0.855 (0.036)	0 (0)	0.953 (0.034)
C11	0.064 (0.050)	0.170 (0.059)	0.943 (0.106)	0.428 (0.07)	0.422 (0.077)	0.913 (0.064)	0.974 (0.067)	0 (0.007)	
C12	0.066 (0.048)	0.179 (0.06)	0.933 (0.118)	0.428 (0.07)	0.423 (0.077)	0.912 (0.065)	0.975 (0.067)	0 (0)	1 (0.023)

Notes: This table shows the parameter estimates on the full set of lotteries (calibration plus test set) for the present-value method.

Table 3.72: Overview parameter estimates on full sample (48 lotteries)

Parameter Estimates for the Time-separation Method (All Lotteries)

Table 3.73 shows the parameter estimates (with standard errors in parentheses) for the time-separation method. The labels C1 to C12 refer to the combinations as in Table 3.4. Combinations C1 to C6, thus, summarize the parameter estimates for the model combinations that employ power utilities as basic utility functions. Combinations C7 to C12 summarize the parameters for the model combinations that employ exponential utilities as basic utility functions. The coefficients for exponential utility (α and β) are multiplied by a factor of 1000.

Combination	Value		λ	$\gamma+$	Weighting		$\nu-$	Discounting	
	α	β			$\gamma-$	$\nu+$		r	k
C1	1.037 (0.032)		1.255 (0.134)	0.791 (0.086)	0.76 (0.090)			0 (0)	
C2	1.032 (0.034)		1.224 (0.131)	0.788 (0.085)	0.764 (0.090)			0 (0)	0.96 (0)
C3	1.077 (0.046)		1.245 (0.189)	0.73 (0.113)	0.699 (0.130)	1.038 (0.046)	1.025 (0.050)	0 (0)	
C4	1.049 (0.045)		1.116 (0.140)	0.751 (0.110)	0.694 (0.130)	1.003 (0.043)	0.978 (0.045)	0 (0)	1 (0)
C5	1.047 (0.031)		1.164 (0.135)	0.745 (0.108)	0.686 (0.128)	0.893 (0.057)	0.895 (0.072)	0 (0)	
C6	1.033 (0.032)		1.118 (0.140)	0.754 (0.108)	0.687 (0.127)	0.913 (0.057)	0.912 (0.071)	0 (0)	1 (0)
C7	-0.012 (0.043)	-0.034 (0.056)	1.1468 (0.096)	0.828 (0.065)	0.806 (0.071)			0 (0)	
C8	-0.014 (0.042)	-0.034 (0.057)	1.155 (0.097)	0.829 (0.064)	0.808 (0.071)			0 (0)	1 (0)
C9	0.1 (0.08)	0.15 (0.053)	1.109 (0.093)	0.807 (0.087)	0.758 (0.120)	0.921 (0.049)	0.897 (0.033)	0 (0)	
C10	0.0916 (0.079)	0.1508 (0.054)	1.104 (0.105)	0.802 (0.086)	0.755 (0.120)	0.922 (0.050)	0.897 (0.033)	0 (0)	1 (0)
C11	0.09 (0.074)	0.148 (0.054)	1.138 (0.106)	0.78 (0.099)	0.7305 (0.125)	1.025 (0.044)	1.0417 (0)	0 (0)	
C12	0.0986 (0.074)	0.1486 (0.053)	1.098 (0.091)	0.7736 (0.098)	0.7128 (0.124)	1.021 (0.045)	1.041 (0)	0 (0)	1 (0)

Notes: This table shows the parameter estimates on the full set of lotteries (calibration plus test set) for the time-separation method.

Table 3.73: Overview parameter estimates time-separation method (48 lotteries)

Parameter Estimates for the Monetary Present-value Method (All Lotteries)

Table 3.74 shows the parameter estimates (with standard errors in parentheses) for the monetary-present value method. The labels C1 to C12 refer to the combinations as in Table 3.4. Combinations C1 to C6, thus, summarize the parameter estimates for the model combinations that employ power utilities as basic utility functions. Combinations C7 to C12 summarize the parameters for the model combinations that employ exponential utilities as basic utility functions. The coefficients for exponential utility (α and β) are multiplied by a factor of 1000.

Combination	Value		Weighting				Discounting	
	α	β	λ	$\gamma+$	$\gamma-$	$\nu+$	$\nu-$	r k
C1	1.179 (0.075)		1.133 (0.227)	0.579 (0.040)	0.592 (0.058)			0 (0)
C2	1.182 (0.072)		1.141 (0.224)	0.576 (0.041)	0.576 (0.058)			0 (0)
C3	0.886 (0.065)		1.05 (0.206)	0.415 (0.070)	0.432 (0.082)	0.78 (0.071)	0.774 (0.097)	0.073 (0.039)
C4	0.889 (0.047)		1.075 (0.192)	0.427 (0.068)	0.449 (0.082)	0.782 (0.058)	0.789 (0.063)	0 (0.002)
C5	0.915 (0.049)		1.033 (0.223)	0.403 (0.068)	0.406 (0.075)	1.036 (0.097)	1.05 (0.112)	0.041 (0.023)
C6	0.915 (0.049)		1.087 (0.200)	0.406 (0.069)	0.421 (0.074)	1.03 (0.096)	1.05 (0.118)	0.001 (0.009)
C7	-0.092 (0.075)	-0.096 (0.066)	1.115 (0.224)	0.634 (0.034)	0.646 (0.043)			0 (0)
C8	-0.074 (0.079)	-0.0852 (0.062)	1.11 (0.232)	0.628 (0.033)	0.639 (0.048)			0 (0)
C9	0.174 (0.048)	0.208 (0.054)	1.147 (0.2)	0.427 (0.068)	0.452 (0.083)	0.834 (0.046)	0.841 (0.035)	0.038 (0.021)
C10	0.174 (0.049)	0.222 (0.053)	1.138 (0.175)	0.428 (0.068)	0.456 (0.082)	0.829 (0.046)	0.836 (0.036)	0 (0.001)
C11	0.196 (0.054)	0.226 (0.050)	1.151 (0.186)	0.429 (0.070)	0.441 (0.074)	0.996 (0.061)	1.023 (0.071)	0.018 (0.019)
C12	0.198 (0.054)	0.218 (0.051)	1.12 (0.187)	0.41 (0.067)	0.429 (0.074)	0.993 (0.063)	1.0246 (0.071)	0 (0.005)

Notes: This table shows the parameter estimates on the full set of lotteries (calibration plus test set) for the monetary present-value method.

Table 3.74: Calibration monetary present-value method (all combinations)

Components of PT (Time-separation Method)

Figure 3.22 displays the prediction performance of different Time-Separation models that either i) include all PT components, ii) force linear probability weighting, iii) force no loss aversion, or iv) force a linear utility. The prediction performances of models with a linear utility or no loss aversion are almost identical to the performance of full PT models. Also models that force linear-probability weighting predict decisions only a bit worse than full PT models.

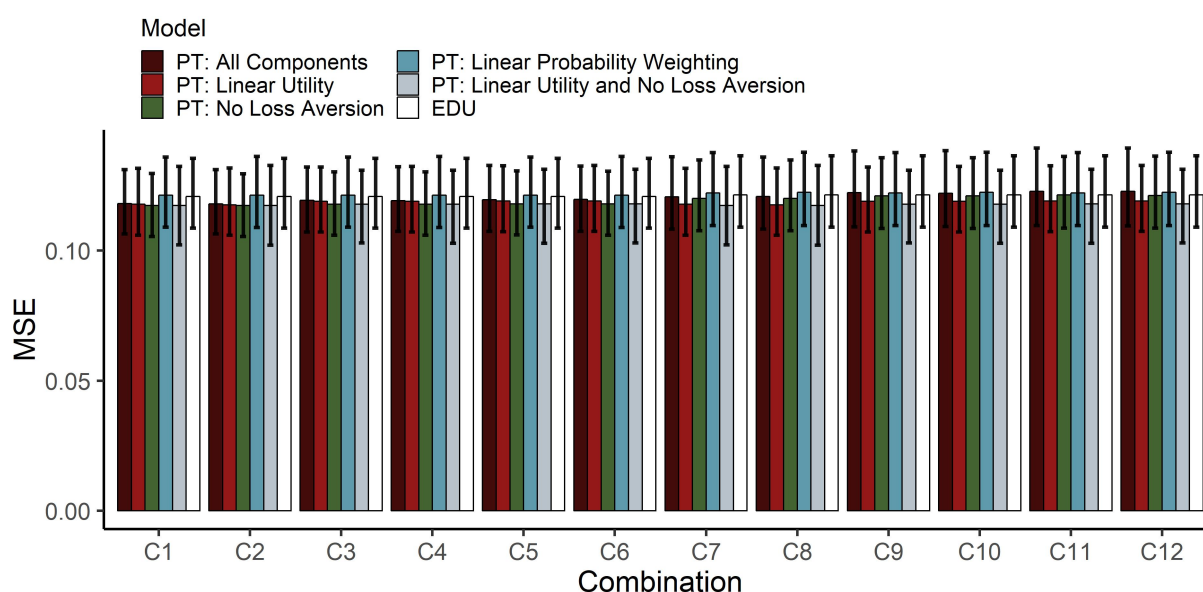


Figure 3.22: MSE time-separation method, PT components (all function combinations)

Notes: This figure compares the prediction performance of the time-separation method to versions of it with some components absent and to expected utility theory (parameters are estimated anew for each method). The versions are (from left to right for each of the 12 function combinations) the monetary present-value method with all components ('PT: All Components'), with linear utility for gains and losses still including a loss-aversion parameter ('PT: Linear Utility'), with a loss-aversion parameter of 1 ('PT: No Loss Aversion'), with linear-probability weighting ('PT: Linear Probability Weighting'), with linear utility for gains and losses and a loss-aversion parameter of 1 ('PT: Linear Utility and No Loss Aversion'); on the right expected discounted utility is shown ('EDU').

Components of PT (Monetary Present Value Method)

Figure 3.23 displays the prediction performance of different Monetary-Present-value Models that either i) include all PT components, ii) force linear probability weighting, iii) force no loss aversion, or iv) force a linear utility. The prediction performances of models

with a linear utility or no loss aversion are almost identical to the performance of full PT models. However, for models that force linear-probability weighting the prediction performance becomes a lot worse.

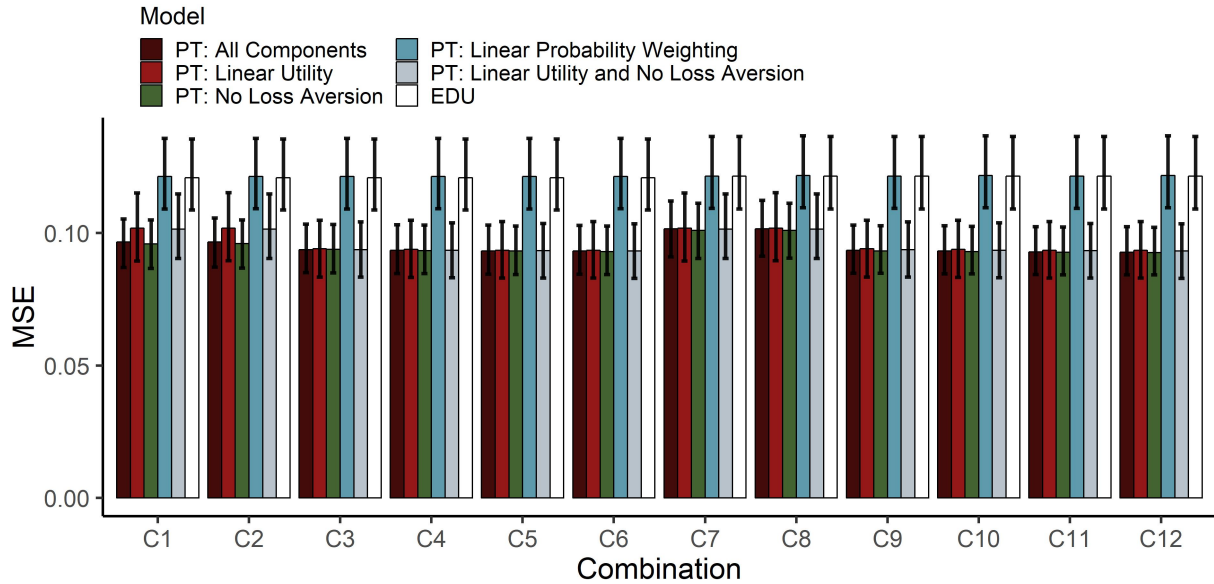


Figure 3.23: MSE monetary present-value method, PT components (all function combinations)

Notes: This figure compares the prediction performance of the monetary present-value method to versions of it with some components absent and to expected utility theory (parameters are estimated anew for each method). The versions are (from left to right for each of the 12 function combinations) the monetary present-value method with all components ('PT: All Components'), with linear utility for gains and losses still including a loss-aversion parameter ('PT: Linear Utility'), with a loss-aversion parameter of 1 ('PT: No Loss Aversion'), with linear-probability weighting ('PT: Linear Probability Weighting'), with linear utility for gains and losses and a loss-aversion parameter of 1 ('PT: Linear Utility and No Loss Aversion'); on the right expected discounted utility is shown ('EDU').

Treatment Comparison

Table 3.75 summarizes mean evaluations for lotteries of Set 1 and Set 4 (the two sets of gain lotteries) of participants in the incentivized and hypothetical treatment. Different statistical test (exact Schlag tests, as pre-registered, as well as t-tests and Wilcoxon-Mann-Whitney tests) do not show any significant differences in evaluations.

Lottery	Mean evaluation		Schlag-tests		t-tests		WMW-Tests	
	T1 (Hyp.)	T2 (Inc.)	p	Adj. p	p	Adj. p	p	Adj. p
L1	10.18	10.26	1	1	0.97	0.97	0.79	1
L2	13.07	10.37	0.71	1	0.12	1	0.09	1
L3	17.07	18.78	1	1	0.33	1	0.21	1
L4	16.12	15.04	1	1	0.48	1	0.39	1
L5	14.55	12	0.78	1	0.14	1	0.06	0.9
L6	15.47	15.89	1	1	0.79	1	0.87	0.87
L7	13.48	12.04	1	1	0.34	1	0.24	1
L8	27.75	28.93	1	1	0.45	1	0.5	1
L33	188.32	175.41	1	1	0.73	1	0.75	1
L34	239.64	206.78	1	1	0.31	1	0.52	1
L35	349.58	390.44	0.94	1	0.2	1	0.23	1
L36	293.27	299.52	1	1	0.83	1	0.86	1
L37	262.08	249.22	1	1	0.72	1	0.47	1
L38	279.15	274.56	1	1	0.88	1	0.57	1
L39	208.48	233.63	1	1	0.4	1	0.41	1
L40	540.44	570.7	0.99	1	0.34	1	0.26	1

Notes: This table shows mean evaluations for lotteries of Set 1 and Set 4 (the two sets of gain lotteries) of participants in the incentivized and hypothetical treatments. Simple p -values are denoted by p , Bonferroni-Holm-adjusted p -values are denoted by Adj. p .

Table 3.75: Evaluation of gain lotteries in T1 and T2

Contract
Information

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RESEARCH INTEREST

Primary: behavioral economics, experimental economics
Secondary: household finance, development economics

EDUCATION

2017 - Ph.D. in Economics and Finance University of St. Gallen
2017 M.Sc. in Business Mathematics, Ulm University
2016 M.Sc. in Mathematics, University of Wisconsin Milwaukee
2014 B.Sc. in Business Mathematics, Ulm University

MEDIA WRITINGS

Senkt ein hoher Selbstbehalt die Gesundheitskosten? APA-Science (2019), WPZ Forschungsnachrichten (2019)

PUBLICATIONS

Loss Aversion and the Demand for Index Insurance
Immanuel Lampe and Daniel Würtenberger (2020). Journal of Economic Behavior & Organization

OTHER RESEARCH PROJECTS

Intertemporal Prospect Theory
Immanuel Lampe and Matthias Weber

Demand for Long-Term Care Insurance: Time Preferences Matter, Risk Preferences Don't