Subjective information in economic decision making

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PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Katholieke Universiteit Brabant, op gezag van de rector magnificus, prof. dr. F.A. van der Duyn Schouten, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op

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door

ALBERTUS CHRISTIANUS DOROTHEA DONKERS

geboren op 11 april 1973 te Tilburg

PROMOTOR: Prof. dr. A.H.O. van Soest
COPROMOTOR: Dr. B. Melenberg

Voor mijn ouders

Things are not.......

.......what they seem to be

Preface

This dissertation presents the results of the project 'Het toetsen van levencyclusmodellen van financieel gedrag' financed by the Netherlands Organization for Scientific Research (NWO). Chapters 2 and 3 have already been published elsewhere and I would like to thank the editors of the *Journal of Economic Psychology* and the *Review of Income and Wealth* for their permission to include slightly modified versions of the published articles in this dissertation. The research presented in Chapters 2, 3, and 4 was done in cooperation with Arthur van Soest (for Chapter 2), Marcel Das (for Chapter 3), and Bertrand Melenberg and Arthur van Soest (for Chapter 4). Funding for visits to conferences and workshops was provided by the Netherlands Organization for Scientific Research (NWO), the Training and Mobility of Young Researchers (TMR) project on savings and pensions, and the Department of Econometrics at Tilburg University. The data used in this dissertation come from the CentER Savings Survey (CSS) and were kindly provided by CentER.

Acknowledgment

This dissertation is the result of four years work at the Department of Econometrics and CentER at Tilburg University. The environment at Tilburg University has always been a very pleasant and stimulating one, mainly due to the colleagues that were around in Tilburg during those four years. I am really grateful to Arthur van Soest and Bertrand Melenberg for their supervision in the past four years. In the numerous meetings we had, they showed me how to do scientific research, paying attention to both the theoretical and practical aspects. Even though they are not mentioned as co-authors for all the chapters, they have made substantial contributions to the shape of each of them. For Chapter 3 this also holds for Marcel Das, who co-authored this chapter.

A nice thing about the Department of Econometrics is the broad range of subjects covered by the researchers. It has certainly stimulated my interest in different fields in economics. Fortunately, it was not only research that was point of discussion. For all those social talks I would like to thank in the first place my roommate, Franc Klaassen, but also Jenke ter Horst and Rob Euwals, whose discussions I often followed and joined, even though they were in the room next door. Finally, there are a number of people with whom I often went for a coffee. One of them deserves to be mentioned explicitly, namely, Miranda.

I do not want to take the risk of forgetting anybody, so I will not start with a list of names of people who made my stay in Tilburg a pleasant one. However, without deep thinking more than a dozen names come to my mind. Thanks to all of you. I am also grateful to Rob Alessie, Michael Haliassos, Arie Kapteyn, and Peter Wakker for their willingness to be a member of the thesis committee.

Although my colleagues made it a nice environment to work in, I owe at least as much to my parents, who supported me in good and bad times. The last two years they shared this task with my girlfriend, Cynthia, who turned out to be very good in it. It must have been difficult for them to listen to somebody talking about problems that he cannot solve, while they could not do anything else than listen.

Bas Donkers
Tilburg, March 2000

Contents

Chapter 1

Introduction

Individual and household decision making plays a central role in economics. In this thesis we discuss the use of subjective information in the empirical analysis of economic decision making. The subjective information that we consider in this thesis includes the individual rate of time preference, the level of risk aversion, but also subjective expectations about future income. The economic decisions concern savings and investment decisions, or the decision to buy a house or not. We define subjective information as information that cannot be measured without asking respondents directly. This type of information contrasts with objectively verifiable information, like the individual's age, his or her annual net income, and the individual's marital status.

In general, we can distinguish at least three types of subjective information, namely information about the individual's current situation, information about the individual's stated preferences in choice situations, and information about the individual's expectations of future events. The usefulness of subjective information about preferences arises mainly from the fact that we cannot collect all the objective information needed to identify individual preferences in a satisfactory way. Individuals' expectations are by definition subjective, since they cannot be verified objectively. When subjective information on individual preferences or expectations is available, this information can be used in empirical analyses to construct instruments that control for otherwise unobserved heterogeneity. Three cases of subjective information are extensively studied in this thesis, namely income expectations, a measure of impatience or time preference, and measures for risk attitudes.

First we describe a few situations where subjective information can play an important role. The rate of time preference, for example, is important in all types of investment decisions. Two investment decisions, that play a major role in economic models of behavior in a life cycle context, are the savings decision, which is the decision to investment in future instead of current consumption, and the schooling decision, which is the decision to invest in human capital and higher future earnings, at the cost of lower current earnings. It has already been shown in the literature (Hansen and Belzil (1999)) that, if one wants to estimate the returns to schooling, it is important to correct for unobserved heterogeneity due to variation in subjective discount rates. If a direct measure of impatience is available, one can use this information to control for the otherwise unobserved heterogeneity. Also in models for saving behavior, direct information on the rate of time preference or the level of risk aversion can be used to improve the analysis. The use of such information may not only improve the fit of an empirical model, but it can also have large consequences for the analysis of, for example, government policies based on the model. Suppose that the government is interested in increasing savings for old age and that a researcher has found a positive correlation between the level of education and savings, after controlling for income. In this case the government might conclude that stimulating educational investment will help to increase savings. However, it is possible that the observed correlation between education and savings is caused by the fact that more patient individuals have invested more in their education and also save more. In this situation, the extra education does not necessarily increase the individual's level of patience, so there might be no effect on savings. When subjective information on individual rates of time preference is available, one would be able to discriminate between the direct effect of education on savings, which the government can manipulate, and the effect of patience on savings, which is not necessarily influenced by a government policy.

Information about income expectations is useful in the analysis of saving behavior in general, but specifically in the analysis of precautionary saving, where information on the individual's perceived income uncertainty is very important, see Browning and Lusardi (1997). Theoretically it is possible to analyze individual income uncertainty using only observed income realizations. One only has to make assumptions about the expectation formation process. However, for the analysis of a realistic empirical model of income uncertainty, one needs to have a large amount of information about the individual, such as whether the individual wants to quit his job, whether the individual is paid according to a fixed wage scale, etc. Obtaining all the relevant information is practically impossible and the use of subjective information provides a solution to this problem.

The aim of this thesis is to analyze different types of subjective information and to investigate the usefulness of this type of information in a number of problems dealing with economic decision making. The first part of this thesis deals with an analysis of the usefulness of subjective information in empirical models of economic decision making. This analysis is conducted using the CentER Savings Survey,[1] which is a rich data set containing questions on many aspects of individual preferences and expectations, but also information on income, family composition, asset holdings, etc. A description of the dataset and the data collection method is given in Nyhus (1996). The CentER Savings Survey is well suited for our analysis and it is used extensively in the other chapters of this thesis. We investigate whether the empirical relationships between observed economic decisions and the subjective measures of time preference, risk aversion, and interest in financial matters reflect what economic theory predicts. An example of such a relationship is that more risk averse individuals are less likely to own risky assets. The conclusion from this analysis is that the relationships between the subjectively measured quantities and the decisions we analyze are in line with the predictions according to economic theory. From this, we conclude that incorporating subjective information in empirical models of economic decision making is useful.

The second part of this thesis deals with the analysis of some of the subjective information that is present in the CentER Savings Survey. Previous studies that tried to measure time preference or risk attitudes have come to the conclusion that the answers to questions on risk aversion or time preference are in contradiction with the models that are traditionally used in the field of economics, such as the expected utility model (von Neuman and Morgenstern (1944)) and the discounted utility model (Samuelson (1937)). In the economic psychology literature, theories have been developed that are more capable of describing observed behavior. In

[1] This survey started as the VSB-Panel, which was sponsored by the VSB foundation.

this thesis we will make extensive use of these theories. For the analysis of the questions on risk aversion we use Cumulative Prospect Theory, which is developed by Tversky and Kahneman (1992). The time preference questions are analyzed using the model of Loewenstein and Prelec (1992). These two models have in common that they are reference dependent. This means that individuals do not evaluate new situations as a whole, but as deviations from a reference point, which is usually the initial situation. The empirical analysis of the risk aversion and time preference questions in Chapters 4 and 5 clearly shows that individuals do not seem to behave according to the discounted expected utility paradigm. This observation motivated the theoretical analysis of individual consumption and portfolio choice patterns in a structural dynamic framework. The individuals' utility function is reference point dependent and the individuals do not maximize expected utility, but subjectively weighted utility. This analysis is presented in the third part of this thesis, Chapter 6. We continue with a more detailed overview of each chapter in this thesis.

In Chapter 2 we start with a detailed analysis of three individual characteristics that are subjective in nature. These three characteristics are the subjective rate of time preference, a measure of risk aversion, and a measure of interest in financial matters. In the second part of Chapter 2 we use these three characteristics and a set of objectively measurable variables in an analysis of the home ownership decisions of Dutch households and the related decisions on the value of the house and the amount of mortgage to take. Furthermore, we investigate how these characteristics are related to the ownership of risky assets, such as stocks and options.

The first subjectively measured individual characteristic is the individual's level of impatience. This is measured with the subjective discount rate that is used by the individual to postpone an imaginary lottery prize for one year. The individuals are asked how much money they want to receive in addition to the imaginary prize they won, if they have to wait one year before they will receive the prize. If an individual wants a compensation of 10% of the prize for waiting one year, then his subjective discount rate is set at 10% per year. Our empirical analysis reveals that the subjective discount rate is related to the respondent's age, where older people are more patient. Of the other variables we included, such as gender and income, none was significant. The amount of variation in the rate of time preference that is explained by age is limited. The question that remains is whether this is because the answers to such questions are mainly noise or that they contain genuinely new information. This question can be answered with the results in the second part of Chapter 2.

Economic theory predicts that more impatient individuals are less likely to own a house, since more impatient individuals are more likely to face binding liquidity constraints and are also less interested in the long term benefits, that are due to the repayment of the mortgage. The empirical results from the analysis of the home ownership decision indicate that the subjective measure of the individual rate of time preference has a negative effect on the home ownership rate, which is what economic theory predicts. From this we conclude that the answers to the questions on subjective discount rates indeed contain new and relevant information about individual preferences.

The second characteristic we consider in Chapter 2 is a measure of risk aversion. This measure of risk aversion is derived from a question on whether the respondent thinks it is more important to have safe investments and guaranteed returns than to take a risk to have a chance to get the highest possible returns, or not. Here we find that females are more risk averse than males and older individuals are more risk averse than younger ones. Again the amount of variation that we can explain with other observed characteristics is rather small. This measure of risk aversion is used in the explanation of the home ownership decision and the other related decisions. Moreover, we also relate it to the decision to own risky assets, in which it should play an important role. Risk aversion is not very influential in the housing decisions, except for a small negative effect on the value of the house. With respect to the decision to own risky assets we find that individuals that are more risk averse, according to the subjective measure of risk aversion, are less likely to own risky assets. This effect is highly significant and has a substantial size. Thus, it is possible to infer relevant information about risk aversion using subjective information and use such information in empirical models of economic decision making.

The answer to a question on interest in financial matters is the third characteristic that is analyzed in Chapter 2. Although this characteristic is not directly related to a concept in economic theory, it is an individual characteristic that could be influential in the type of decisions we consider. The results show that individuals with more interest in financial matters are more likely to own a house, which is, on average, also more expensive. Furthermore, they are also more likely to own risky assets.

The main conclusion that we can draw from Chapter 2 is that subjective information may be very useful for predicting and explaining economic behavior. However, in this chapter we use only one question to measure each of the concepts we consider, while the CentER Savings Survey contains a large number of questions on both time preference and risk aversion. The questions on risk aversion are analyzed in Chapter 4. In that chapter we use a reduced form semiparametric model, but we also estimate a structural model of the individual decision making process. The time preference questions are analyzed with a structural model in Chapter 5. In the later waves of the panel a set of questions has been included that deals with the respondent's perception of the distribution of his household's income in the next year. The answers to these questions are analyzed in Chapter 3.

The questions on individual's perceptions of next year's net household income in the CentER Savings Survey are similar to the questions that are used by Dominitz and Manski (1997). The first two questions ask about the range of next year's (uncertain) household income. Then four questions are asked about the probabilities that household income will fall below a certain value in the specified range. From these four questions we can derive points of the respondent's subjective distribution function of next year's household income. In Chapter 3 we focus on two characteristics of this perceived distribution, which are the median and a measure of relative income uncertainty, which we define as the ratio of the interquartile range of the subjective income distribution and the median of this distribution.

We relate the median of the subjective income distribution to some other observed individual and household characteristics, such as the labor market status of the household members and past household income. The effects of different labor market characteristics are substantial, where the most interesting finding is that the influence of household income in the previous period on the expected level of next year's income is smaller if this income is earned by both the head of the household and the partner. We also investigate the relationship between our measure of relative income uncertainty and the labor market status of the household. Here, we also include the respondent's perceptions of past income changes and expectations about future income changes. It is interesting to see that perceptions about past income changes do not influence perceived income uncertainty, while expected changes in income increase the perceived level of income uncertainty. Finally, a comparison is made between perceived income uncertainty in The Netherlands, in Italy, and in the US. Perceived income uncertainty in Italy is a bit lower than in The Netherlands, but this difference is rather small. From a comparison of the two European countries with the US we conclude that perceived income uncertainty in the US is substantially higher than in Italy and in The Netherlands.

In Chapter 4 we empirically analyze individual attitudes towards risk. In this chapter we do not use the same measure of risk aversion as in Chapter 2. Our analysis is based on a set of eight questions on lotteries. In five of these questions the respondents are asked to choose between two lotteries, while the remaining three questions are probability equivalence questions, where the respondents are asked to give the probability of winning a prize for which they are indifferent between the lottery and a fixed amount of money.

We take two different approaches to the data on risk attitudes. We start with a reduced form approach, where we semiparametrically estimate a single index model and interpret the index as a measure of risk aversion. With this approach there is no need for strong assumptions about the decision making process and about the way respondents answer the questions. The disadvantage of reduced form models is that they do not make it possible to predict behavior in different situations, or to understand the differences in the decision making process that result in different answers. To gain more insight in the decision making process we also estimate a structural model.

The expected utility paradigm seems a good starting point when one wants to construct a structural model of decision making under risk. However, as already noticed, there is a substantial amount of evidence that the expected utility model does not result in a good description of the individual's choices between lotteries. The large amount of systematic deviations from expected utility that are observed has led researchers to develop alternative models for decision making under risk and uncertainty. One of the most frequently used theories in this field is Cumulative Prospect Theory (Tversky and Kahneman (1992)). This theory differs from expected utility in two ways. First, according to Cumulative Prospect Theory, individuals do not use the objective probabilities, but decision weights, that depend on the probabilities and on the ranking of the outcomes. The decision weights are constructed from a transformation of the distribution function of the outcomes. This transformation is done with the probability weighting function. Second, the outcomes are evaluated as deviations from a certain reference point. The function that attributes the values to the outcomes is called the value function. It replaces the utility function in the expected utility model.

Our empirical model is based on Cumulative Prospect Theory. We choose a particular parameterization of the value function and the probability weighting function and estimate the unknown parameters using the answers to the probability equivalence questions. Our estimation results show that the hypothesis of expected utility maximization is strongly rejected, given our parameterization of the value function, but there is little variation in the way different individuals transform the probabilities. With respect to risk aversion we find that females and older people are more risk averse, while income and wealth have a negative relationship with risk aversion.

In Chapter 5 we analyze how individuals make decisions in an intertemporal setting. We focus on decisions in very simple situations, like the compensation that an individual requires for postponing an imaginary payment for one year. The traditional way of modelling such decisions is with the discounted utility model. As already noticed, many researchers claim, based on experimental evidence, that this model does not describe behavior very well, see, among others, Thaler (1981) and Green et al. (1997). The general conclusion is that discount rates depend on the amount of money, the time span, whether it is a gain or a loss, and whether the payment is delayed or not. A limitation of the analyses of these experiments is that they focus on the implicit discount rates applied to the outcomes, while respondents discount the utility of the outcomes and not the outcomes themselves.

We estimate a structural model for the individual's decision making process, which is based on the model of Loewenstein and Prelec (1992). We do not restrict the way in which the discount factor varies with the length of the time interval. The utility attributed to the outcomes is allowed to be reference dependent. The results we obtain are not what we expected a priori. We find slightly negative discount rates, on average, while at first sight our data imply high positive discount rates. The driving force behind this result is the effect of loss aversion in the decision making process. Although losses are weighted only a few percent heavier than gains, this has a large impact on the observed discount rates. To check these rather counterintuitive results, we compare the predictions of the model with the data. The model fits the data rather well. We allow the parameters in the model to vary with observed characteristics. We find that the discount rate is lower for females and older people. Income also has a negative relationship with the discount rate. The variation in the level of loss aversion is negligible.

In the chapters on risk aversion and time preference it turned out that reference points are very important in the individual decision making process. In the literature on saving and investment decisions, however, there is only little attention for reference points, except for models that incorporate habit formation. Moreover, data from many experiments show that models in which individuals use decision weights perform substantially better in describing behavior than models where objective probabilities are used, see Gonzalez and Wu (1999), among others. In Chapter 6 we investigate the consequences of probability weighting and reference dependence with loss aversion on the optimal consumption, savings, and investment decisions of individuals in a structural dynamic life cycle model. Preferences that incorporate loss aversion or probability weighting display first order risk aversion, as it is defined by Segal and Spivak (1990).

The equity premium puzzle is the fact that the observed difference in returns of a risky and a relatively riskless asset is so large that it cannot be explained with a representative agent model without incredibly high levels of risk aversion. This puzzle has been raised by Mehra and Prescott (1985). The microeconomic counterpart of the equity premium puzzle is the stock holding puzzle (Haliassos and Bertaut (1995)), which is the fact that one cannot explain the low holdings of risky assets by households, given the high expected returns of the risky asset compared to the risk free rate of return. It is argued by Epstein and Zin (1990) that preferences with first order risk aversion might be able to solve the equity premium puzzle. For this reason preferences with probability weighting or loss aversion are possible solutions for the equity premium puzzle and the stock holding puzzle.

We consider the optimal consumption, investment, and savings decisions for agents with a number of preference specifications that differ with respect to the level of loss aversion, the type of probability weighting, and the shape of the utility function that is used. For each preference specification we determine the optimal consumption, savings, and investment paths for a large number of individuals with identical preferences. Each individual receives different draws from the modelled income and asset return processes. If the individuals' preferences have probability weighting, we find that the optimal portfolio weight given to the risky asset is substantially lower than when the individuals' preferences are based on expected utility. Thus probability weighting provides a possible solution to the stock holding puzzle and, consequently, the equity premium puzzle.

When loss aversion is incorporated in the preference specification we also observe lower optimal portfolio weights for the risky assets, but this effect is a lot smaller than the effect of probability weighting. However, for the consumption and savings decisions the opposite holds: We find a strong effect of loss aversion, while the effect of probability weighting is rather small. When loss aversion is important, individuals save more than otherwise, but they also hardly dissave after retirement. Thus, loss aversion might be an explanation for the low dissavings of the elderly that is observed in real life, but which is difficult to explain with traditional economic models.

The analysis in Chapter 6 shows that preferences with loss aversion and probability weighting can play in important role in our understanding of economic phenomena, but maybe the most important lesson that can be learned from this thesis is that economists can learn a lot from economic psychologists.[2]

The final chapter is forward looking. It discusses the ways in which the results of the research presented in this thesis can be used. It also deals with ways to improve the information gathering process. Finally, it discusses some of the important open questions that remain in this broad field of research and for some of these questions it discusses possible ways to answer them.

[2] Of course, the reverse statement is also likely to hold.

Chapter 2

Subjective measures of household preferences and financial decisions

In intertemporal models of household consumption or portfolio choice, household behavior depends on, for example, the household's rate of time preference, the level of risk aversion, and the household's information set. In this chapter we use a survey of Dutch households which contains direct subjective information on risk aversion, time preference, and interest in financial matters. We first describe these data and analyze how they relate to household characteristics and household income. We then investigate whether these variables are related to households' financial decisions on home ownership, mortgages and ownership of risky assets. Our results are broadly in accordance with economic theory.

2.1 Introduction

In models of household consumption or portfolio choice, household preferences play an important role in various ways. Mainstream economic theory of household consumption and saving behavior is based upon the life cycle hypothesis (see, e.g., Deaton, 1992, and Browning and Lusardi, 1996). Here household preferences depend, among other things, on the rate of time preference and the household's level of risk aversion. In the standard two period Markowitz model of portfolio choice (Markowitz, 1952), the choice between holding risky and risk–free assets will depend on the agent's risk aversion parameter. In extensions of this model, the rate of time preference also plays a role. See, for example, the model of

Henderson and Ioannides (1983), which explains household consumption and investments in financial as well as housing wealth.

In empirical studies in the above fields, direct information on the household's rate of risk aversion or time preference is never used, at least to our knowledge. The reasons are twofold. First, such information is usually not available. We know of no previous survey with information on portfolios or savings and consumption in which this type of subjective information is present. Second, according to Dominitz and Manski (1997), many economists are sceptical about the use of information based upon subjective survey questions in general. In various recent studies however, subjective information on income expectations is used (Guiso et al., 1992, 1996, for example), suggesting that the tide is changing.

In this chapter we use two waves of a panel survey of Dutch households drawn in 1993 and 1995. This data set has two properties which make it particularly useful for our purposes. First, it contains detailed information on many asset and liability holdings, including home ownership and mortgages. Second, it contains a number of 'psychological' variables. These contain subjective information which can be used to measure household preferences directly. We shall use three such variables, measuring time preference, risk aversion, and the household's interest in financial matters.

The first purpose of this chapter is to describe these data, to analyze their internal validity (i.e., to see whether sample distributions of the psychological variables make sense), and to see to which extent they can be explained from household characteristics and household income. The second purpose is to investigate whether these variables are helpful in explaining households' financial decisions. An extensive study of debts and assets of Dutch households was carried out by Ritzema and Homan (1991). They analyze economic, sociological, and psychological explanations using cross section data for 1988. They do not use the type of psychological variables that we have here, however. We focus on decisions related to home ownership and mortgages. As in many countries, investment in (owner occupied) housing is the most important component in household portfolios in The Netherlands. On average, it represents more than 60 percent of households' gross assets (see Alessie et al., 1997, for example). Similarly, mortgage debt is by far the largest type of liability: more than 80 percent of all debts is mortgage debt (Alessie et al., 1997). We also consider the choice whether or not to hold risky financial assets. While more than 80% of Dutch households hold financial assets, less than 10% hold risky assets like stocks and bonds. Why few people hold stocks and bonds has been the topic of studies for other countries (see Haliassos and Bertaut, 1995). Here we can test directly whether holding risky assets is related to the head of household's subjectively measured level of risk aversion.

Throughout the chapter, we rely on static reduced form univariate models. The equations explain financial decisions from subjectively measured variables and other household characteristics, and we do not address the issue of potential endogeneity of subjective variables. The conceptual model we have in mind is therefore rather straightforward: household characteristics (family composition, income, labor market status) are given, household preferences (time preference, interest in financial matters, risk aversion) may vary with these characteristics, and household financial decisions (home ownership, value of owned housing, mortgage, portfolio choice) are driven by family characteristics and preferences. This conceptual model may be overly simplified, but given the limitations of our data, and particularly the short length of the panel, we feel we cannot identify much more at this stage. A structural model for consumption and investment decisions is presented and analyzed in Chapter 6 of this thesis.

The main question in this chapter is whether the correlations we find can be explained from economic theory. In most cases we find that they can, even when other variables are controlled for. This leads to the conclusion that subjective information is valuable in estimating structural models of economic household behavior, in which endogeneity, dynamics, and causal relationships should be taken into account.

As argued above, our findings are of interest for empirical economic research of household behavior under uncertainty, in a life cycle context, or both. They should help to improve our knowledge of the heterogeneity among household preferences which is relevant for household decision making. They are also of potential interest to marketeers of banks and insurance companies, etc., who may use our type of results to design new products which optimally fit consumer preferences, such as specific types of mutual funds, life insurances, private pension plans, or mortgages. They can also use the results to address their marketing efforts for specific products to groups of households whose preferences are such that they will, on average, be most interested in buying these products.

The remainder of this chapter is organized as follows. In Section 2.2, we present a brief description of the data in general. Then we analyze the subjective measures of time preference, risk aversion, and interest in financial matters. Emphasis is put on the rate of time preference, which can be measured in different ways, based upon nine different questions in the survey. In Section 2.3, we consider the home ownership decision, using a binary probit model. In Section 2.4, we explain the value of the house, conditional on home ownership, using linear regression. In Section 2.5, we explain the mortgage as a fraction of the purchase value of the house, again conditioning on home ownership. Here we use a censored regression model, to take account of the fact that many home owners do not have a mortgage. In Section 2.6, we analyze financial wealth holdings with emphasis on the choice between risky and riskfree assets. Section 2.7 concludes.

2.2 Data and description of subjective variables

We use two waves of the CentER Saving Survey, the first wave, drawn in 1993, and the third wave, drawn in 1995. The 1994 wave was drawn only a few months after the 1993 wave, and contains little new information for our purposes. Nyhus (1996) describes the set up of this data set and its general quality. She also discusses the possible sample bias due to nonresponse problems. Daniel (1994) uses the first wave of this data set and specifically focuses on time preference variables.

The panel consists of two subpanels. The first is representative of the Dutch population, the other one is designed to represent households in the upper 10% of the income distribution. We will refer to the two subpanels as the representative panel (REP) and the high income panel (HIP), respectively. All households participating have been provided with a personal computer and answer the survey questions directly on their PC; no personal interviews are held. The questionnaires contain various sections: household characteristics, housing, labor market status and pension entitlements, health, income, and assets and liabilities. Not all households have answered the questions in all sections. The subjective variables we are interested in are contained in the psychological section. In 1993, 2,258 of the 2,775 households in the panel have completed this section, and 2,251 of these have completed all sections of the questionnaire. Usually, the questions are answered by the head of household. In some cases, the partner has answered the psychological questions, and the head has not. In these cases we use the partner information (and her background variables such as age and education level). In 1995, 2,037 of the 2,766 households answer the questions in the psychological section, and 2,035 of them have completed all sections of the questionnaire. Thus in both years, nonresponse to the psychological questions was quite large, as also mentioned by Daniel (1994) and Nyhus (1996). Due to item nonresponse on mainly income (for 20%, household income could not be computed), psychological questions (about 28% in 1993, 21% in 1995), or assets (about 22% in 1993 and 1995), the data set is further reduced to 1,155 households in 1993 and 1,275 in 1995. The representative panel has 651 observations in 1993 and 822 in 1995, the high income panel 504 and 453. Some item nonresponse in the psychological questionnaire is due to a question on risk aversion which is only asked if net household income is above Dfl. 20,000 (about $ 10,000).

In this section, we pay attention to some variables derived from the subjective information in the questionnaire. These variables are the household's subjective interest rate, a measure of risk aversion, and a measure of interest in financial matters. Variables related to housing assets will be discussed in the next sections. The appendix to this chapter contains some details on the background variables we use. In the figures, which we present to describe the data, we will use the 1995 data, except for the figures on interest in financial matters. All figures for the 1993 sample are similar to those for 1995, and we therefore do not present them.

2.2.1 Subjective interest rates

The survey collects information on how individuals evaluate a delay or speed-up of receiving or paying a certain amount of money. In total, nine (series of) questions are asked, differing on the following points (the codes that we use to name the variables are mentioned in parentheses)

- The money is payable in the future and the question refers to how much the household is willing to sacrifice to get the money now (S: speed-up), or the amount is payable immediately and the question refers to the additional amount the household requires to compensate for postponing the payment to some later point of time (D: delay).

- The household will receive the money (G: gain) or has to pay (L: loss).
- The time period that is covered: 3 months (03) or 12 months (12).
- The amount of money that is at stake: Dfl. 1000 (1) or Dfl.100,000 (100).

In the first waves of the survey nine out of the sixteen possible combinations are used (see Table 1 below). The waves from 1997 onwards contain all 16 questions. A structural analysis of these questions in presented in Chapter 5. The precise wording of, for example, the question DG12100 is as follows.

Imagine you win a cash prize in a lottery. The prize is worth Dfl 100,000 and can be paid out AT ONCE. Imagine the lottery, which is a financially trustworthy organization, asks if you are prepared to wait a year before you get the prize. Would you agree to that proposal, or would you ask for more money if you had to wait for one year. What would you prefer:

1. *I would agree to the waiting term of a year without requiring extra money for that. So after a year I receive Dfl 100,000.*
2. *I would agree to the waiting term of a year, but I want to receive extra money for that.*

If the respondent wants extra money, the following question is asked:

How much extra money would you want to receive AT LEAST, in addition to the Dfl 100,000?

For the households requiring extra money for waiting on the payment, the subjective interest rate is calculated from the questions mentioned above as $r = \frac{\text{extra amount of money}}{100{,}000}$.

For households willing to wait without requiring additional money, we set the rate of time preference to zero. This concerns almost 6% of all households, see Table 2.1. It could be the case that the 'true' rate of time preference for these households is negative. An explanation might be that households want to restrain themselves from spending all the money at once, i.e., are prepared to pay a premium to enforce self-control (cf. the theory in Shefrin and Thaler, 1988, and the empirical evidence in Kahneman and Thaler, 1991). The wording of the two other questions of the DG type are very similar, but lead to a much larger fraction of zero subjective interest rates (see Table 2.1).

Table 2.1: Subjective interest rates

	1993		1995	
Interest rate	Fraction[a]	Mean[b]	Fraction[a]	Mean[b]
DL121	0.116	0.064	0.118	0.059
DL031	0.066	0.115	0.058	0.106
DG12100	0.943	0.086	0.941	0.085
DG03100	0.868	0.112	0.864	0.110
DG031	0.717	0.204	0.727	0.189
SG121	0.393	0.070	0.302	0.071
SG031	0.155	0.122	0.127	0.109
SG12100	0.500	0.053	0.453	0.053
SG03100	0.263	0.086	0.231	0.073

[a]Fraction of respondents who chose the second option and answered the follow-up question on the amount.
[b]Only for those who answered the follow-up question.

The first SG question (SG031) was:

Imagine you win a cash prize in a lottery. The prize is worth Dfl 1,000 and will be paid out in three months time. The lottery offers you to pay out the price immediately, but then you will receive a smaller amount of money. What would you prefer:

1. *I will wait for three months and receive Dfl 1,000 then.*

2. *I want the money now and accept a smaller amount.*

Only those who choose the second option answer a follow-up question similar to that in the DG case:

How much less than Dfl 1,000 would you accept if the amount is paid now?

The other SG questions and the DL questions are similar. The first question does not specify how much the speed-up premium will be. Thus individuals who choose to wait do not necessarily prefer to receive the same amount later to receiving it now. This is different from the DG questions, which are formulated more precisely. Table 2.1 reveals that the majority of individuals choose the first option and do not answer the question on the amount. These people may or may not prefer costless speeding up; Shelley (1993) extends the framing theory of Loewenstein (1988) and shows that in case of loss aversion it is possible that people with a positive rate of time preference prefer waiting to costless expediting. The explanation is that, compared to the original situation, expediting leads to a current loss and a future gain. The fact that losses are weighted heavier than gains may dominate the time preference. See Daniel (1994), who uses the same data as we do, and links the differences between the questions to various theories in economic psychology. (She works with individuals as units of observations, while we will work with households.)

Table 2.1 also presents the means of the positive rates, with the three months answers transformed into annual rates. The means tend to be somewhat smaller in 1995 than in 1993. Together with the larger numbers of zeros this suggests that respondents in 1995 are more patient. The ordering of the means of the various questions remains the same. The rates based on the three months questions tend to be higher than those from the twelve months questions.

For the questions of the DG type, choosing the first option in the first question can be interpreted as a zero or negative subjective interest rate. The correlation between the subjective interest rates according to these three questions in both years, with zeroes for those who chose the first option, are shown in Table 2.2. They are all significantly positive at the 5% level, and all but one at the 1% level. In the remainder of this chapter we focus on the interest rate derived from DG12100, which refers to postponing payment of a realized gain, the largest amount of money, and the longest difference in timing. It has the smallest number of zeroes and its mean value seems plausible, although lower values of our measure of time preference could be expected if risk aversion and/or loss aversion were taken into account (see Shelley, 1993).

Table 2.2: Correlation coefficients between observed interest rates (including zeroes).

	1993			1995		
	DG12100	DG03100	DG031	DG12100	DG03100	DG031
DG12100(93)	1	0.60	0.25	0.19	0.19	0.13
DG03100(93)	0.60	1	0.47	0.14	0.22	0.20
DG031(93)	0.25	0.47	1	0.08	0.12	0.23
DG12100(95)	0.19	0.14	0.08	1	0.61	0.35
DG03100(95)	0.19	0.22	0.12	0.61	1	0.38
DG031(95)	0.13	0.20	0.23	0.35	0.38	1

The estimated probability density of the subjective interest rate based upon this question in 1995, for the two panels REP and HIP separately, is depicted in Figure 2.1. The households with a zero subjective interest rate are not included. This figure is drawn using non-parametric kernel density estimation (see Härdle and Linton, 1994; the choice for the value of the smoothness parameter is based on visual inspection of the figures, the quartic kernel is used).

The figure suggests that the density is bimodal, with modes at about 5% and 10%. In the HIP, the average rate (excluding the zeroes) is somewhat larger than in the REP (8.3% with standard error 0.3% in REP, versus 8.5% with standard error 0.3% in HIP in 1995 and similar in 1993).

Nonparametric regressions of the subjective interest rate on log family income and on age are shown in Figure 2.2 (zeroes included; REP 1995 only). The figures suggest that the subjective interest rate is not related to income, and negatively related to age.

To test whether this remains to be the case if other background variables are controlled for, we explain the subjective interest rate using a standard tobit model:

$$\begin{aligned} y^* &= x'\beta + \epsilon \\ y &= max(y^*, 0) \\ \epsilon &\sim N(0, \sigma^2), \quad \epsilon \text{ and } x \text{ independent} \end{aligned}$$

Here y^* is a latent variable, y is the observed subjective interest rate, β is a vector of unknown parameters, ϵ is an error term, and x is a vector of explanatory variables. We used age, gender, and family income variables, dummies for education

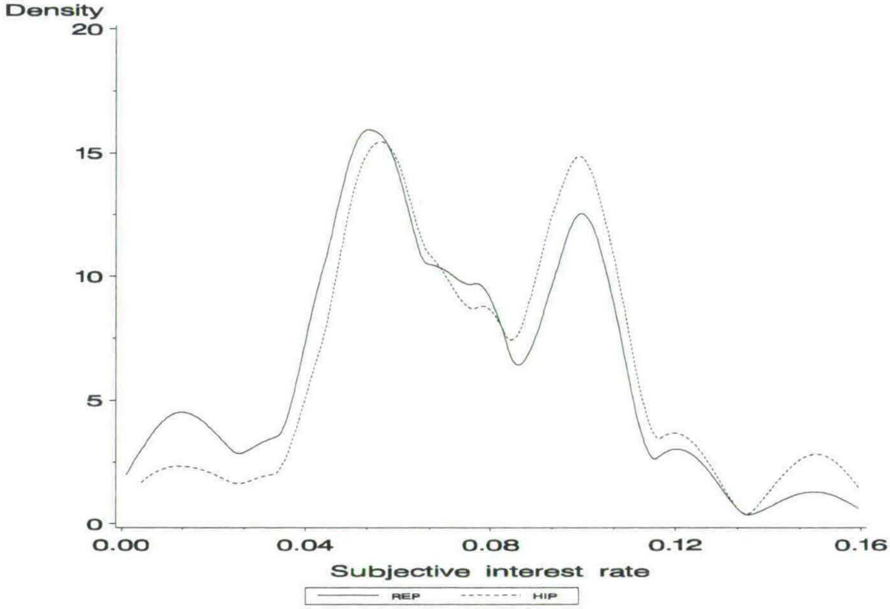

Figure 2.1: Estimated probability density of the subjective interest rate

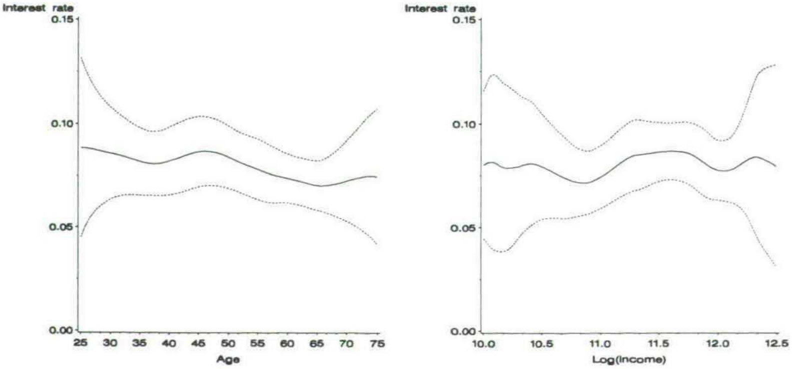

Figure 2.2: Estimated regression functions for the subjective interest rate

levels, family composition and employment status variables. After eliminating the variables that are insignificant, the only variables that remain are log age and gender (i.e., a dummy which is 1 for females and 0 for males). The slope coefficients for log age are (standard errors in parentheses) -0.019 (0.007) in 1993 and -0.018 (0.008) in 1995. Thus older people tend to be more patient. Thaler and Shefrin (1981) already expected this, since younger people yet have to master the techniques of self–control. The coefficients on the dummy for females are -0.024 (0.005) in 1993 and -0.014 (0.005) in 1995, implying that women tend to be more patient than men. The tobit regressions had very small R^2 values (0.02 in 1993, 0.01 in 1995), indicating that only a small part of the variation in the subjective interest rates can be explained by family characteristics and other background variables. (The R^2 in the Tobit model is defined as the estimate of $\frac{V\{x'\beta\}}{V\{x'\beta\}+\sigma^2}$, the explained part of the variance of y^*.)

2.2.2 Risk aversion

The value of the variable Riskaverse is the answer to the following question:

I think it is more important to have safe investments and guaranteed returns than to take a risk to have a chance to get the highest possible returns.

Disagree Strongly						Agree Strongly
1	2	3	4	5	6	7

Heads of household who agree strongly with this statement are not willing to take financial risks and are thus considered to be very risk averse.

The correlation between the risk aversion variable measured in 1993 and 1995 for the same households is 0.40 (and significant at any conventional level). The distribution of outcomes for the two subpanels in 1995 are shown in Figure 2.3. Risk aversion in the representative panel is more dispersed than in the high income panel, with more very risk averse people as well as more people who are not risk averse at all. The average value is about 5.1 for both panels in both years.

Figure 2.4 shows the results of nonparametric regressions of Riskaverse on log family income and age, including uniform 95% confidence bands (REP 1995 only). No significant relation with income can be detected, but the figure suggests that risk aversion increases significantly with age.

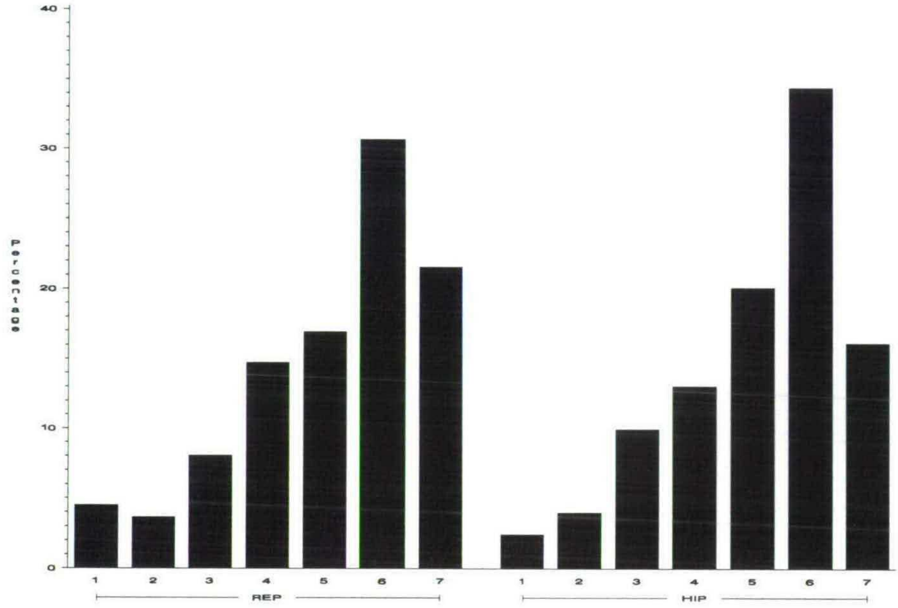

Figure 2.3: Percentage of answers in each category for Riskaverse

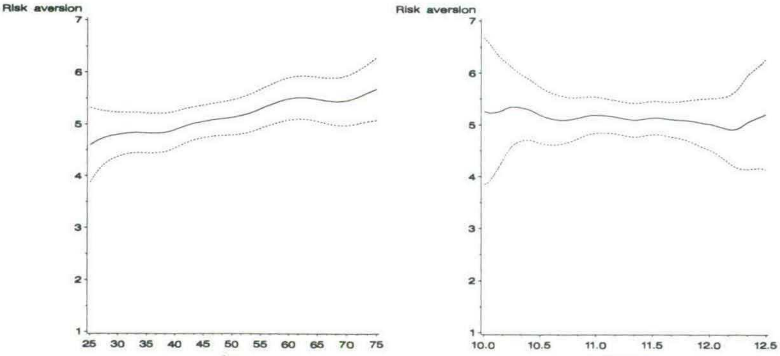

Figure 2.4: Estimated regression functions for Riskaverse

Table 2.3: Ordered Probit Estimates for Riskaverse

	1993		1995	
Variable	Estimate	Std. Err.	Estimate	Std. Err.
Constant	10.251	4.937	3.423	5.384
Log(Age)	-6.057	2.684	-1.428	2.860
Log^2(Age)	0.888	0.354	0.296	0.374
Log(Income)	0.116	0.056	-0.067	0.058
Female	0.267	0.075	0.205	0.076
m_2	0.391	0.050	0.347	0.048
m_3	0.789	0.061	0.809	0.060
m_4	1.273	0.066	1.288	0.065
m_5	1.774	0.070	1.771	0.068
m_6	2.590	0.075	2.697	0.075
R^2	0.05		0.05	

To check whether these relations still hold if we control for other characteristics, we explain Riskaverse using an ordered probit model. The model is as follows.

$$
\begin{aligned}
&y^* = x'\beta + \epsilon \\
&y = j \text{ if } m_{j-1} < y^* \leq m_j \quad (j = 1, ..., 7), \\
&\epsilon \sim N(0,1), \quad \epsilon \text{ and } x \text{ independent.}
\end{aligned}
$$

Here y is the observed answer, the category bounds are $-\infty = m_0 < m_1 < \ldots < m_6 < m_7 = \infty$. By means of normalization, m_1 is set to zero. $m_2, \ldots, m_6$ and the vector β are the parameters to be estimated. The model is estimated using maximum likelihood. In this model the observations of REP and HIP are combined. The results for both years are presented in Table 2.3, for a specification which only retains variables that are significant in at least one of the two years. The R^2 value (using the same definition as in the tobit model) of 0.05 in both years shows that the amount of variation we can explain is rather small, but we are better able to explain risk aversion than time preference.

Log age and log age squared are jointly significant in both years. The 1993 estimates imply that risk aversion increases from the age of 30, the 1995 estimates imply that risk aversion rises with age over the whole range. This might be a pure age effect or a cohort effect. Women are more risk averse than men, on average.

Log income is significantly positive in 1993, but negative and insignificant in 1995. The traditional literature on the theory of portfolio allocation suggests that relative risk aversion decreases with wealth, while absolute risk aversion increases with wealth (see Arrow, 1965, or Pratt, 1964). If household income is seen as a proxy for wealth, our result can be reconciled with this if household heads interpret the question in a relative sense: the amount they have in mind for a 'safe investment' is some share of their income or wealth.

Income risk reduces the portfolio risk one is willing to take. This corresponds to Guiso et al. (1996) who find a negative relation between income uncertainty and investment in risky assets. It leads to an increase of our measure of risk aversion. This implies that the measure of risk aversion we use depends on the family's circumstances and income uncertainty, and does not reflect underlying preferences only. In that sense, it does not measure the 'true' risk aversion of the household's utility function, unconditional on labor market or health status. A drawback of our measure thus may be that it not only determines, but also depends on the family's financial decisions. It is not clear whether a 'true' measure which does not suffer from this problem can be obtained; this would require much more from the wording of the questions and the respondents' ability to answer them.

2.2.3 Financial interest

For the question on interest in financial matters the same answering scheme was used as for the risk aversion variable. The exact question was:

I am very interested in financial matters (insurances, investments, etc.).

```
Disagree Strongly                                    Agree Strongly
             1      2      3      4      5      6      7
```

This question was asked in 1993 only; the 1995 survey does not contain any question on this issue. The distributions of the answers to this question in 1993 are presented in Figure 2.5 for HIP and REP separately. On average, the high income panel participants are more interested in financial matters than the households in the representative panel.

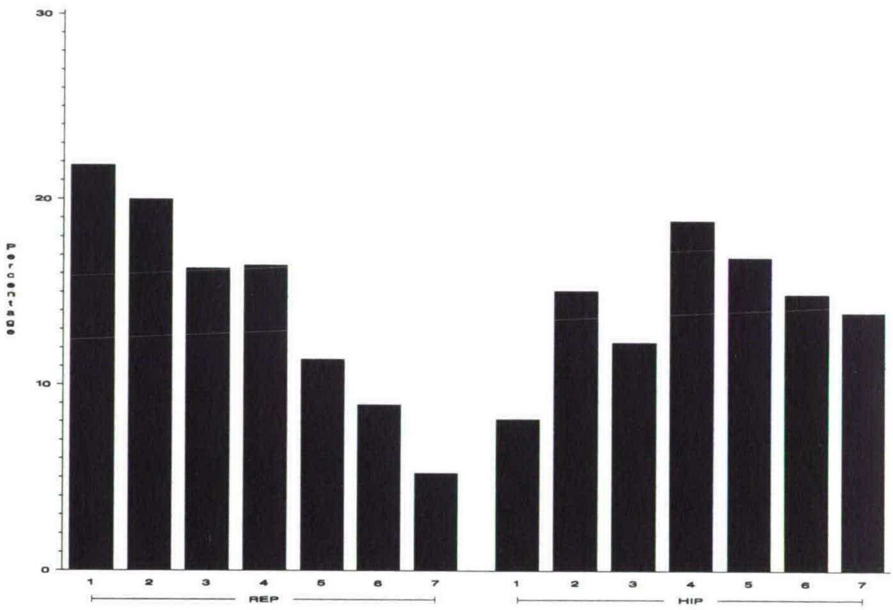

Figure 2.5: Percentage of answers in each category for Finint

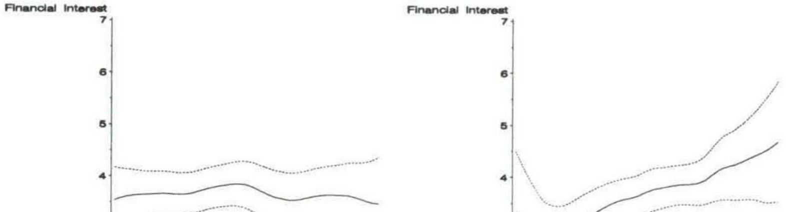

Figure 2.6: Estimated regression functions for Finint

Nonparametric regression results for the representative panel are displayed in Figure 2.6. Finint and age are not related, but there is a positive relation between Finint and income. An ordered probit model reveals the relationship between interest in financial matters and various control variables. The specification is similar to that for risk aversion. Results are presented in Table 2.4. The value of the R^2 is a bit larger than the one for Riskaverse, but still rather low. Log age was retained in the model, though it appeared to be insignificant.

Table 2.4: Ordered Probit Estimates for Finint

	1993	
Variable	Estimate	Std Err.
Constant	-1.807	0.733
Log(Age)	-0.087	0.106
Log(Income)	0.308	0.056
Married	0.122	0.084
Female	-0.324	0.074
m2	0.602	0.038
m3	0.989	0.045
m4	1.452	0.050
m5	1.883	0.056
m6	2.412	0.065
R^2	0.06	

Women tend to be less interested in financial matters than men. Log income has a substantial positive impact, which can explain the difference between REP and HIP in Figure 2.5. Different explanations for this finding can be given. First, high income families have more investment and portfolio allocation opportunities, and will therefore get more interested in financial matters. Second, people with a large interest in financial matters may have a stronger preference for income compared to leisure or job characteristics than others. Therefore they more often accept the best paying job, and choose their portfolio efficiently to maximize asset income.

2.3 The choice between owning and renting

One of the most important financial decisions a household makes is the choice to buy a house or not. Wealth invested in the own house is by far the largest asset category in The Netherlands. All remaining households in the data answered the question whether they rented or owned their house. The exact question is:

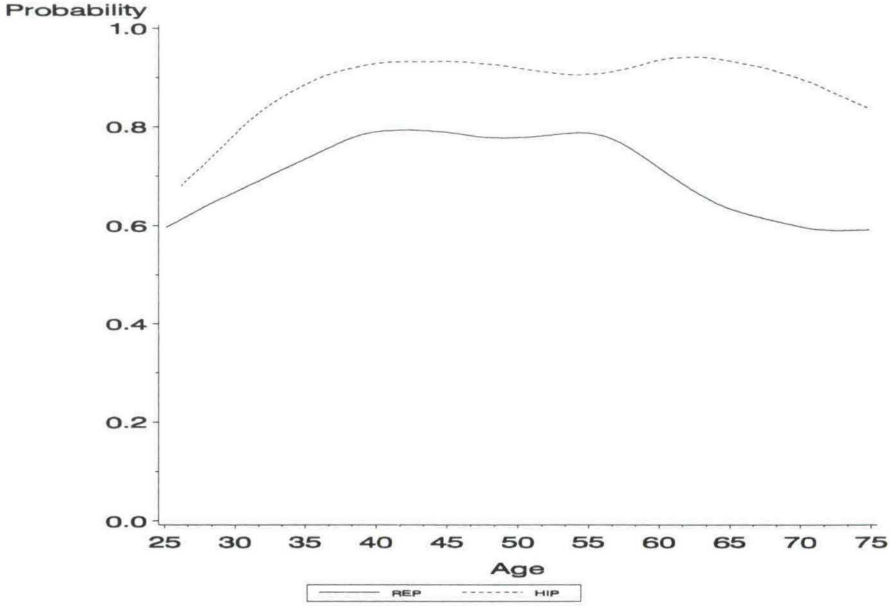

Figure 2.7: Probability that a household owns its house

Are you tenant, subtenant or owner or do you rent for free? If you live in more than one house, please report the most important one.

The largest group of households own a house, 66.5% of the households in the 1993 REP (71.8% in 1995) and 91.9% of the households in the 1993 HIP (90.7% in 1995). 28.0% of the 1993 REP (33.0% in 1995) households are renting, while 0.5% (0.2% in 1995) are subtenants. We merge the subtenants with the renters. In Figure 2.7 the probability that a household owns its residence is depicted as a function of age of the household head. The curve is smoothed using the same nonparametric regression techniques as in the previous section. The solid line refers to the 1995 REP, the broken line to the 1995 HIP. The probability of owning in the representative panel is hump shaped. It increases until about age 40, and decreases from age 55.

In general the choice between renting and owning will depend on income and wealth, on the possibility to obtain a mortgage, on expected returns to housing and financial assets, on family composition, household preferences, etc. See, for example, Henderson and Ioannides (1983) for a theoretical model. Since many of the variables which would play a role according to theory were not measured, we do not consider structural models. Instead, we estimate a reduced form equation and focus on the impact of the variables discussed in the previous section. The rate of time preference and the risk aversion rate are features of household preferences. Since owning a house generally requires a large investment expenditure at the time the house is bought, the probability of home ownership can be expected to decrease with the rate of time preference. The same holds for the risk aversion measure: due to variation in housing prices, the returns to housing are usually more uncertain than average financial assets, particularly since in The Netherlands, few households hold risky assets such as stocks or bonds. The bulk of financial assets are saving accounts which are practically riskfree. (See Section 2.6 for details). Moreover, the cost of renting is largely fixed, while ownership costs may include a large fraction of uncertain maintenance costs. Finally, it is generally assumed that in the long run and on average, owning is cheaper than renting, also because of the tax rules which make owning relatively attractive. This makes it likely that households with more interest in financial matters own more often than others. It could also be argued that causality works in the other direction here: families who have taken a mortgage were forced to show some financial interest at that time.

The choice between renting and owning is modelled with a standard probit model. Thus the probability that a household owns its house equals $\Phi(x'\alpha)$, where $\Phi(.)$ is the standard normal distribution function and α is the vector of parameters to be estimated. The model is estimated with maximum likelihood. The results are presented in Table 2.5. For 1995, the financial interest variable is not available. To obtain comparable results, we therefore also present the 1993 results without the variable Finint. The R^2 values, defined in the same way as in the tobit and ordered probit models in Section 2.2, show that we can explain a reasonable part of the variation in homeownership rates.

The probability of ownership increases with age of the head of the household. The joint effect of log age and log age squared is significant, as is shown by a likelihood ratio test. Household income has a strong positive effect, as could be expected. Families with at least one working member (Work=1) have a larger probability of owning than families consisting of nonworkers only. If the head of the household has a partner (Married=1), this increases the probability of

Table 2.5: Estimation results for the home ownership decision

	1993		1993		1995	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Constant	-42.607	7.121	-41.816	7.093	-38.767	7.946
Log(Age)	19.078	3.876	18.535	3.861	16.765	4.234
Log^2(Age)	-2.477	0.517	-2.406	0.515	-2.148	0.560
Log(Income)	0.556	0.090	0.599	0.089	0.541	0.088
Married	0.358	0.113	0.373	0.112	0.560	0.116
Work	0.063	0.135	0.061	0.135	0.335	0.132
Workp	0.291	0.114	0.292	0.113	0.021	0.103
Riskav	0.014	0.027	0.020	0.027	0.038	0.026
Subint	-1.273	0.616	-1.110	0.615	0.934	0.632
Finint	0.086	0.024	——	——	——	——
R^2	0.28		0.26		0.21	

ownership. If the partner also has a job (Workp=1), the probability of owning a house increases even more. The significance levels of these variables are rather different for 1993 and 1995, however.

The estimate for the variable Finint indicates that people who are more interested in financial matters are more likely to own their house. This is consistent with our prior expectations given above: in the long run owning is cheaper than renting, mainly because interest on mortgages is fully tax-deductible, interest on financial assets is taxed apart from a small tax exempt amount, and capital gains (on housing or other assets) are not taxed at all. People who are more interested in financial matters will be more aware of this.

In 1993, a higher subjective interest rate makes it less likely for a household to own its home. This can be explained by the fact that the short run costs of having a house and a mortgage are higher than the rent for a house with similar characteristics. The payments however are partly used to pay off the mortgage and thus increase wealth. This is a long run effect and people using a high discount rate will give it less weight. A second explanation is that households with a higher discount rate are more likely to face binding liquidity constraints, making it harder for them to buy a house. Surprisingly, the subjective interest rate has the opposite sign in 1995, though it is significant at the 10% level only.

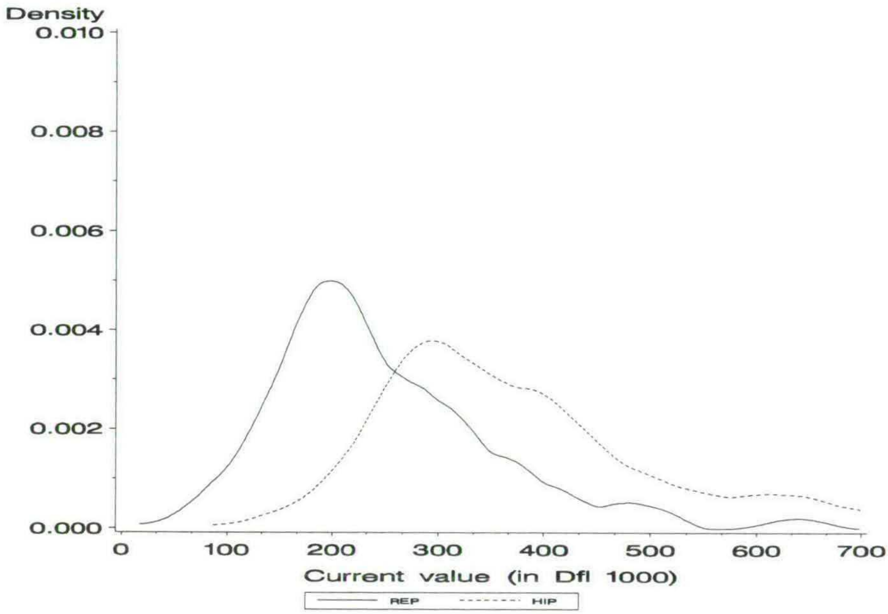

Figure 2.8: Estimated probability density of the current value of the house

The parameter estimate on the risk aversion variable is insignificant and positive for both years. This could indicate that households do not see their house as a risky asset. For example, they may not plan to sell their house in the near future, so that they do not give much weight to uncertainty in future house prices. In the short run, rents may be more uncertain than the cost of owning. Due to the way in which risk aversion is measured, another explanation would also be possible: households owning their house face more risk than renters because of housing price volatility and uncertain maintenance costs, etc. This makes them less willing to take extra risks, and this is what the question on risk aversion refers to. This positive relation (higher risk aversion leads to a smaller ownership probability) and the reverse negative relation could cancel out each other. To investigate this further, it would be necessary to estimate a structural model. This is beyond the scope of this thesis.

2.4 The value of the house

Estimates of the probability densities of the current value of the house for the 1995 REP and HIP separately are given in Figure 2.8. The average current values (home owners only; in 1000 Dfl.) are 231 (REP) and 353 (HIP) in 1993 and 251 (REP) and 386 (HIP) in 1995. The distributions in the REP and HIP are quite different. The distribution is strongly unimodal at about 200,000 Dfl. in the 1995 REP. In the 1995 HIP, this peak is missing. The 95% uniform confidence bands (not shown) do not overlap everywhere, implying that the difference between the densities is significant.

A standard linear model is used to explain the log of the current value of the house, conditional on home ownership, for 1993 and 1995 (HIP and REP combined). The estimated coefficients and the corresponding standard errors can be found in Table 2.6. The adjusted R^2 shows that the model explains about one third of the variation in the value of the house.

Table 2.6: Estimation results for the value of the house

	1993		1993		1995	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Constant	-25.183	5.012	-25.293	5.098	-18.551	4.140
Log(Age)	2.191	1.424	2.286	1.449	2.758	1.510
Log^2(Age)	-0.228	0.190	-0.240	0.194	-0.294	0.200
Log(Income)	0.325	0.025	0.345	0.026	0.374	0.026
Married	0.202	0.047	0.218	0.048	0.055	0.041
Work	-0.039	0.041	-0.041	0.042	-0.018	0.028
Workp	-0.032	0.029	-0.029	0.030	0.259	0.047
Famsize	0.046	0.013	0.043	0.013	0.012	0.012
Sincew	0.014	0.002	0.014	0.002	0.010	0.002
Riskav	-0.003	0.008	-0.006	0.008	-0.019	0.008
Subint	0.050	0.194	0.121	0.197	0.208	0.173
Finint	0.038	0.007	——	——	——	——
R^2	0.36		0.34		0.32	

The value of the house increases with age and with family size. The latter is significant in 1993 only. Married couples own more expensive houses than singles, but in 1995, this is only significant if the partner has a paid job. As expected, the value of the house increases significantly with income, implying that (owned) housing is a normal good. An income rise with 10% increases the value of the house by 3 to 4%. We also included the year the household moved into the house (Sincew). It appears that households who bought the house more recently, have more expensive houses, ceteris paribus. If the desired housing stock increases over the life cycle, this can be explained by heterogeneous adjustment costs.

The estimate for the variable indicating interest in financial matters has a significant positive sign. This suggests that the house is seen as a profitable asset. More risk averse households tend to live in less expensive houses. This effect is significant in 1995. It corresponds to the idea that a house is a risky asset, in which risk averse people will tend to invest less. Finally, the effect of the rate of time preference is positive but never significant. Since we have conditioned on home ownership, there is no reason why the rate of time preference should have an impact.

2.5 The amount of mortgage

Households owning a house have first answered a question on whether or not they have a mortgage. In the 1993 REP and HIP, 77.1% and 89.6% of the home owning families answered affirmatively. The data contain information on the year the mortgage was taken as well as on the year the family moved into its current house.

In Figure 2.9 the relation between the fraction of mortgage taken and the current value of the house is shown. Households without mortgage are not included here. The dotted lines are 95% uniform confidence bands. The figure shows that the fraction of mortgage taken and the value of the house are negatively related.

In Figure 2.10 the estimated density of the fraction of the purchase value of the house taken as mortgage by the households is drawn, together with the 95% uniform confidence bands. In this figure the 1995 REP and HIP are combined since the densities for the two panels are almost identical. Many households take almost the total amount of the value of the house as a mortgage. The probability

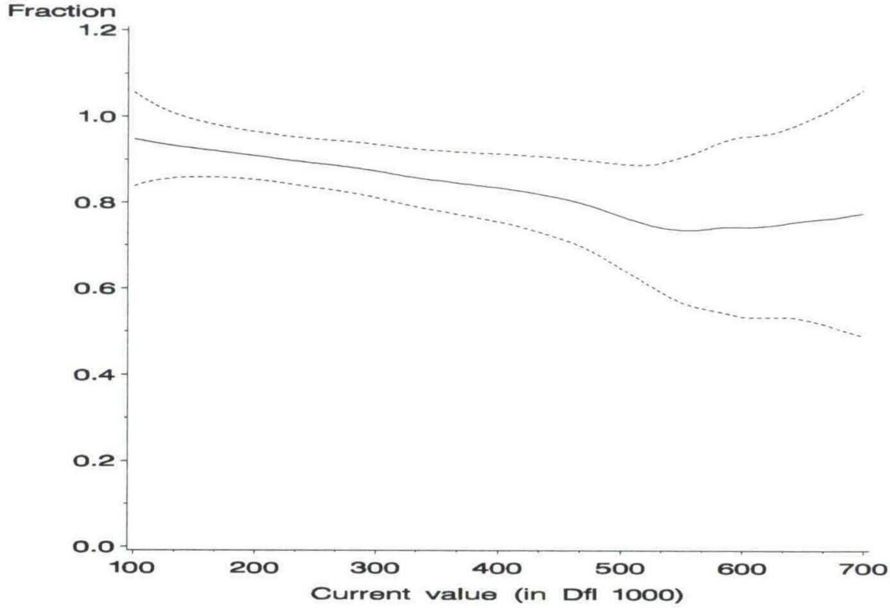

Figure 2.9: Fraction of mortgage as a function of the current value (homeowners only)

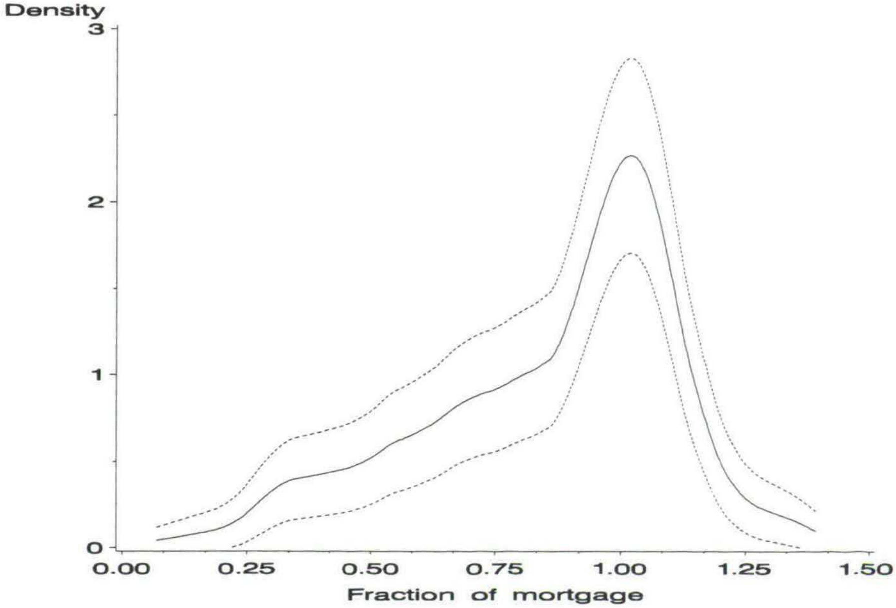

Figure 2.10: Estimated probability density for the fraction of mortgage taken

that the fraction exceeds 1.4 is negligible. A plausible explanation for the fact that there are households with mortgages that substantially exceed the purchase value of the house is that these households used the money to rebuild their house after they bought it. This is confirmed if we compare the difference between the current value and the buying value for those with a higher mortgage with the others. The average yearly increase in the value of the house is more than 2% higher for households with a fraction of mortgage above 1.2. This difference is significant at the 5% level. Very small fractions of mortgage are also rare. Most of the density is concentrated between 0.75 and 1.25. The average fraction is 0.86 in the REP and 0.87 in the HIP (zeroes excluded).

Table 2.7: Estimation results for the fraction of mortgage taken (homeowners only)

	1993		1993		1995	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Constant	-24.394	4.957	-24.235	4.668	-22.674	6.315
Log(Age)	8.964	1.703	8.966	1.707	9.572	1.751
Log^2(age)	-1.274	0.228	-1.275	0.228	-1.341	0.232
Log(Income)	1.544	0.717	1.514	0.719	0.999	0.961
Log^2(Income)	-0.063	0.031	-0.062	0.032	-0.039	0.042
Work	0.050	0.049	0.050	0.049	0.096	0.048
Workp	0.025	0.035	0.023	0.035	0.011	0.032
Married	0.141	0.057	0.137	0.057	-0.027	0.054
Famsize	-0.034	0.015	-0.033	0.015	-0.006	0.013
Riskav	0.006	0.010	0.007	0.010	0.011	0.009
Subint	0.190	0.226	0.163	0.226	0.155	0.193
Finint	-0.015	0.008	——	——	——	——
Sigma(ε)	0.42		0.42		0.39	
R^2	0.27		0.27		0.27	

Since the fraction of mortgage taken by a household will never be negative and there is a positive probability that a household has no mortgage, a tobit model is used to model the fraction of mortgage taken. In Table 2.7, we present the results for 1993 as well as 1995. The R^2 (as defined in Section 2.2) shows that we are able to explain a reasonable part of the variation in mortgage taking behavior.

Conditional on all the other variables, the value of the house was not significant, and we excluded it from the regression. The fraction of mortgage taken increases with age until about age 35, and decreases thereafter. The latter corresponds to the notion that for many people, housing equity is the most important form of saving. Household income has a positive effect on the fraction of mortgage. This could be expected since households with higher incomes will less often face credit constraints and are allowed to pay a smaller downpayment than low income households. The estimated effects of labor market status, marital status and family size appear to be rather different for 1993 and 1995. It should be noted here that labor supply could also be endogenous to the mortgage decision, particularly for married females. Fortin (1995) uses the amount of mortgage remaining to explain female labor supply and finds a significant relationship. She assumes that the amount of mortgage is exogenous, however.

Households with a higher interest in financial matters take a smaller fraction of the value of their house as mortgage than others. The effect of the subjective interest rate is positive but small and insignificant. The rate of risk aversion is also insignificant (and, unexpectedly, has a positive sign).

2.6 Ownership of risky assets

In this section we look at financial assets. We distinguish between riskfree and risky assets. In the risky assets we include stocks, options, and mutual funds. Bonds and bond-related growth funds (safe mutual funds that invest only in bonds) are defined as riskless. Since there are not many households who do not own any form of riskfree assets (checking accounts, saving accounts, deposits, etc.), we focus on the category of risky assets, and in particular on the relation between the decision whether or not to hold risky assets and the subjective variables introduced in Section 2.2. Especially risk aversion is expected to have a strong effect.

In Figure 2.11 nonparametric regressions of the dummy for ownership of risky assets on age, log family income and log wealth are drawn. All variables have a positive relationship with the probability of owning risky assets.

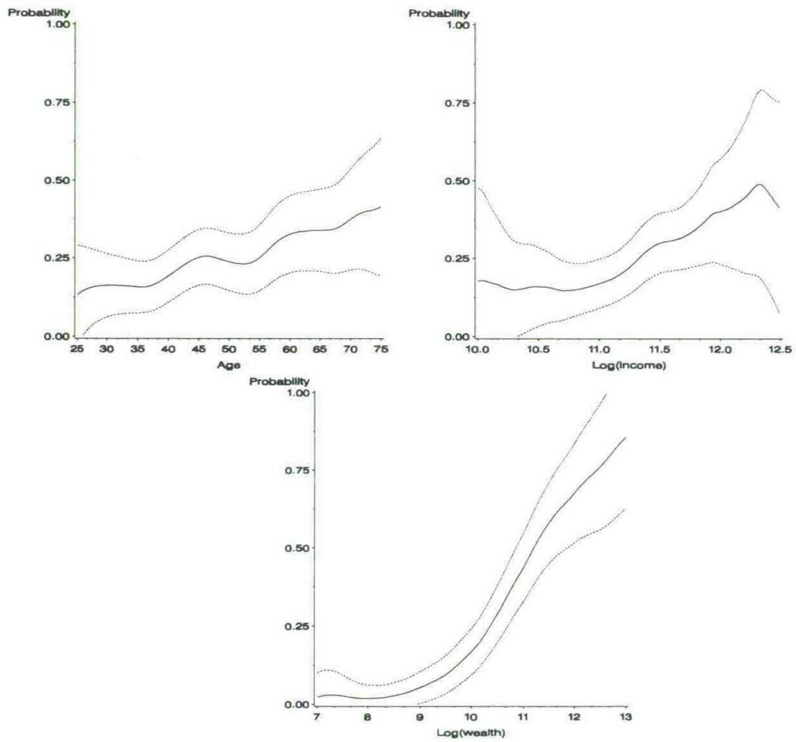

Figure 2.11: Estimated regression functions for ownership of risky assets

A probit model has been estimated to quantify the effects of income, wealth, age and the subjective variables on the probability of owning risky assets. The results are presented in Table 2.8, together with the R^2 for each model. The R^2 values show that the model explains about half of the variation in risk taking behavior.

The age pattern is hump shaped, with a maximum probability of holding risky assets at age 50 (1995 data) or older (1993 data). Log income has a positive sign, but is only significant in 1993. The education dummies imply that investing in risky assets is more likely if the education level is higher. This might be due to the relation with lifetime income and wealth. Moreover, information costs related to investing in risky assets can be negatively related to education level. As expected, the effect of the level of wealth is positive and significant. The pattern corresponds to the convex curve in Figure 2.11.

Table 2.8: Estimation results for ownership of risky assets

	1993		1993		1995	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Constant	-11.842	8.907	-13.484	8.676	-19.400	9.736
Log(Age)	2.467	4.846	3.426	4.720	7.437	5.218
Log^2(Age)	-0.281	0.644	-0.412	0.627	-0.949	0.687
Log(Income)	0.322	0.098	0.362	0.096	0.160	0.098
Edu1	-0.346	0.175	-0.330	0.169	-0.158	0.153
Edu2	-0.418	0.241	-0.453	0.236	-0.534	0.227
Edu3	-0.019	0.144	-0.024	0.140	-0.147	0.136
Edu4	0.031	0.130	0.048	0.126	0.061	0.123
Work	-0.147	0.153	-0.147	0.149	-0.198	0.144
Workp	-0.167	0.112	-0.130	0.108	-0.164	0.101
Log(Wealth)	0.028	0.007	0.029	0.007	0.024	0.006
Log^2(Wealth)	0.018	0.002	0.020	0.002	0.025	0.002
Riskav	-0.098	0.031	-0.105	0.030	-0.062	0.029
Subint	0.100	0.697	0.577	0.656	1.966	0.625
Finint	0.205	0.027	——	——	——	——
R^2	0.51		0.46		0.46	

NOTE: Since some households have negative net wealth, Log(Wealth) is defined as sgn(Wealth)Log(|Wealth|).

The subjective measures of risk aversion and interest in financial matters have the expected signs and are significant. The subjective interest rate has a positive effect, but this is significant in 1995 only. In a simple (life cycle) model of household behavior, the subjective discount rate does not influence the portfolio composition of a household. It only affects the amount of savings; effects caused by different savings attitudes are likely to be taken up by the level of household wealth. If, however, credit constraints are introduced, it could be that households with a higher discount rate, prefer to see these constraints relaxed as soon as possible. These households might then invest in riskier assets with a higher expected return.

We checked the sensitivity of the results for the definition of risky assets.

Defining bonds and growth funds as risky instead of riskless assets gave results similar to those in the table. If (potentially endogenous) wealth variables are excluded from the regressors, the magnitudes of the effects change, but the signs and significance levels of the subjective interest rate, risk aversion and financial interest remain the same. Age, income and education effects change substantially, due to the large correlations between these variables and wealth.

2.7 Conclusions

We have analyzed three subjective measures of household preferences which can influence the household's financial decisions: a measure of the rate of time preference, a measure of risk aversion, and a measure of interest in financial matters. These variables are available in a survey of Dutch households. We have described these variables and we have investigated their relation to family characteristics and income. Second, we have analyzed their contribution to explaining financial behavior related to housing and ownership of risky financial assets.

Rates of time preference can be constructed from various questions in the survey relating to postponing or advancing payments. We find significant positive correlations between the rates constructed from different questions, and between rates in the two panel waves of the survey. This gives us some confidence in the quality of the data. On the other hand, nonresponse is rather large and so is the number of observations with a zero rate of time preference according to some of the questions. This can be the result of the way questions are framed. We focus on the question which gives fewest zeroes, referring to the additional amount somebody wants to receive if a payment of Dfl 100,000 is postponed by one year. The distribution of the household specific rates of time preference constructed from this question seems plausible. Tobit regressions indicate that the rate of time preference is negatively correlated with age, and that women are more patient than men, but most variation in subjective interest rates cannot be explained from individual characteristics. According to the 1993 data, the subjective interest rate has the expected negative effect on the home ownership decision. Conditional on home ownership, however, it has no significant impact on the value of the house or on the mortgage.

Risk aversion is measured by a question on how important people think it is to invest in safe assets compared to aiming at a possibility of high returns. We find that risk aversion increases with age and that women are more risk averse than men. We find a substantial correlation of 0.4 between risk aversion rates in the same households in the 1993 and 1995 wave. More risk averse house owners tend to live in less expensive houses, which corresponds to the idea that the volatility of house prices make a house a risky asset. Moreover, the effect of risk aversion on the decision to invest in risky financial assets is negative and highly significant.

Interest in financial matters is measured on a similar ordinal scale. It increases with income and is larger for men than for women. Interest in financial matters has a strong and significant positive effect on the home ownership decision and on the value of home-owners' houses. This confirms the view that owned housing is seen as a profitable asset. Interest in financial matters makes it more likely for a household to own risky assets.

In general we can conclude that the distributions of the psychological variables and the correlations between them are plausible. The extent to which they can be explained from family characteristics is quite limited. The effects of the subjective variables on financial decisions related to housing and portfolio choice are in some cases quite strong and usually in line with economic theory, though there are some exceptions. The data have clear limitations, as already reported elsewhere (Daniel, 1994, and Nyhus, 1996). Still, we think our results are encouraging enough to conclude that this type of psychological variables are potentially a useful tool for the analysis of household behavior under uncertainty and in a life cycle framework. The questions could also be used in marketing surveys, to better identify groups of households who could be interested in buying financial products such as risky mutual funds (for those with low rate of risk aversion and/or high interest in financial matters), specific long term savings or retirement plans (those with low rate of time preference), etc.

We have used two waves of the panel, and have looked at some correlations over time. Most of the analyses have been carried out for the two waves separately. Though most of our results were similar for the two years, there were also some rather large changes, particularly in terms of significance levels. Using more waves and exploiting the longitudinal nature of the data to a larger extent, should help to interpret these. It then also seems necessary to address the problems of nonresponse and panel selection and attrition. Another direction for future extensions is the use of more psychological questions for measuring the same concepts (such as the rate of risk aversion) or other concepts (such as expected income changes and income uncertainty), which are available in the data set but have not yet been used.

2.A Some details on the data

In Table 2.9, some explanatory variables included in the models are defined.

Table 2.9: Description of explanatory variables.

Variable	Description
Sincew	The year the household moved into their current house.
Work	Dummy; 1 if the head of the household has a job.
Workp	Dummy; 1 if the partner works.
Famsize	Family size.
Kids	Number of children in the household.
Edu1	Dummy; 1 if education level of the head of household is 1.
	The same for Edu2,...,Edu5.
Inchh	Before tax income of the household (ind Dfl.).
Married	Dummy; 1 if the head of the household is married.
Age	Age of the head of the household.
Wealth	Financial wealth of the household (excluding houses and mortgages).

Chapter 3

How certain are Dutch households about future income? An empirical analysis

The precautionary saving literature shows that income uncertainty increases savings and wealth. To estimate the magnitude of this effect, we need a measure of income uncertainty. This paper empirically analyzes subjective income uncertainty in The Netherlands. Data come from a large Dutch household survey. We measure income uncertainty by asking questions on expected household income in the next twelve months. First, we describe the data and investigate the relationship between the measure of income uncertainty and a number of household characteristics. Controlling for information on expected income changes, we find strong relationships between labor-market characteristics and the subjective income uncertainty as reported by the heads of the households. Second, we compare income uncertainty in the Netherlands with income uncertainty in the US and Italy. It turns out that perceived income uncertainty is smaller in The Netherlands than it is in the US.

3.1 Introduction

In the dynamic process of household decision making, expectations about the future play a central role. Common versions of the life cycle and permanent income hypothesis models assert that current consumption depends not only on current wealth, income and preferences, but also on the individual's or household's subjective distribution of future income. On the basis of an empirical study, Carroll (1994) finds that, for fixed permanent income, current consumption is not influenced by predictable changes in future income. However, future income *uncertainty* has an important effect: consumers facing greater income uncertainty consume less.

In the literature on precautionary saving (see Kimball, 1990), several papers have addressed the theoretical result that consumers postpone their consumption when income becomes more uncertain. See, for example, Guiso et al. (1992), Banks et al. (1995), and Lusardi (1997). Portfolio decisions may also be affected by income uncertainty (Kimball, 1993). At an empirical level, this is illustrated by Guiso et al. (1996): the portfolio share of risky assets is inversely related to income risk.

Empirical studies that include income uncertainty face the problem of measuring the (subjective) uncertainty of future income. Some studies use simulations, but as noted by Guiso et al. (1992), simulations do not test whether people actually respond to risk as predicted by the theoretical models. Other studies estimate income uncertainty from panel data on income realizations (see, for example, Carroll and Samwick, 1997). Income changes are then regressed upon individual characteristics and the variance of the residuals is used as a proxy for income uncertainty. Next to assumptions about the expectation formation process, the researcher also assumes that he has the same information as the subjects in the sample, which is rather doubtful. For example, for many individuals yearly salary increases are fixed according to some scale that is known to the individual. Since these wage scales are different for each individual, the wage regression will not be able to explain these differences; the researcher thus observes income uncertainty, while there is in fact no uncertainty at all. The same occurs in the case of a woman who is pregnant and knows she will stop working in five months' time. Her income change is unpredictable in the wage regression, but there is no uncertainty about her income.

A lot of the variation in income changes is thus known to individuals, and is not at all uncertain. In practice, however, it will never be possible to obtain all the relevant information to measure the unpredictable part of income changes. An alternative way to measure income uncertainty is by asking questions about the individual's subjective distribution for income in the next year. This method is less popular among economists. The skepticism is based upon the assertion that people have no incentive to answer the questions carefully. Dominitz and Manski (1997), however, are right in arguing that if this is to be taken seriously, it should be applied to survey data on realizations and not merely to subjective data. Empirical economic analyses of household behavior routinely use self-reports on realized income, assets, employment, and other variables.

Instead of arguing that respondents have no incentive to answer questions about their expectations carefully, one could claim that respondents do not have the ability to answer these kinds of questions. A way to check this is just by analyzing subjective data. Recent work on the subjective measurement of income expectations has indicated that survey data can provide useful information (see, for example, Dominitz and Manski, 1997, and Das and van Soest, 1997, 1999). The latter show that the relations between answers to subjective survey questions on income expectations and various background variables are rather robust over time and have the expected signs.

This chapter focuses on the measurement of subjective uncertainty about future income. First, we want to explore the quality of the data by showing descriptive results. We relate the estimated level of subjective income uncertainty to observed individual and household characteristics. These results give us an idea about the variables that influence income uncertainty. This information may yield some confidence in our measure of income uncertainty if we find plausible relationships, but it can also be used to predict income uncertainty in studies without direct information on income uncertainty. Second, we want to compare our results about income uncertainty in The Netherlands with the results of two other studies that measure uncertainty about future income. We use the study by Dominitz and Manski (1997, DM97 in the sequel) for information on income uncertainty in the US and the study by Guiso et al. (1992) on income uncertainty in Italy.

The data we use come from the third wave of a large Dutch household survey: the CentER Saving Survey. This is the first wave in which questions similar to the ones used by Dominitz and Manski were asked. These questions are concerned with the one-year-ahead income expectations on the household level and provide information about the level and uncertainty of the next year's household income.

We find substantial variation in income uncertainty among households and show that it varies systematically with age, the level of past income, and other observed characteristics. Furthermore, comparing income uncertainty in The Netherlands with income uncertainty in the US and Italy, our results suggest that income uncertainty in The Netherlands is smaller than in it is the US.[1]

The outline of this chapter is as follows. Section 3.2 discusses the questions asked in the CentER Panel Survey to elicit information about subjective income uncertainty. Section 3.3 introduces the way in which we derive a measure of income uncertainty. Section 3.4 estimates a regression model for the location of the subjective income distribution and for the measure of income uncertainty. In Section 3.5, income uncertainty in the Netherlands is compared with income uncertainty in Italy and the US. Section 3.6 concludes.

3.2 Data

The CentER Saving Survey (CSS) started in 1993. The survey method is completely computerized. Each household is provided with a personal computer and a modem. Questions and answers are transferred via the computer. If the respondent has questions or problems, he may call a help desk.

The first two waves of the CSS do not contain the questions we want to use, so we will concentrate on the third wave of the panel. These data were collected in 1995. The CSS consists of two parts. One part is designed to be representative of the whole Dutch population (the 'representative panel'), the other part is a random sample of households in the upper 10% of the income distribution in The Netherlands (the 'high-income panel'). The information in the data set can be divided into seven categories: household characteristics, accommodation, labor-market status and pension entitlements, health, income, assets and liabilities, and economic and psychological aspects of financial behavior. Our analysis draws heavily upon the following categories: household characteristics, income, and economic and psychological aspects of financial behavior. Since not all households participate in all questionnaires, we have 2,189 heads of households instead of the

[1]This conclusion, however, has to be drawn with caution since the survey questions may not be fully comparable because of different wording. Moreover, the sampling methods were not the same.

total of 2,574 heads of households pooled across all questionnaires.[2] A detailed description of the CSS is given in Nyhus (1996).

Within the set of questions we use, the respondents are first asked about the range in which their household income will fall in the next twelve months. The precise wording of these questions is as follows:

What do you think is the LOWEST level your net household income could possibly be over the next twelve months?
and
What do you think is the HIGHEST level your net household income could possibly be over the next twelve months?

After answering these two questions, the respondents are asked to evaluate the probability (in percentage terms) with which their household income will fall below a certain level. Four questions of this type are asked, where the levels referred to in these questions are evenly spread over the interval ranging from the household's reported lowest possible income to its reported highest possible income.[3] The precise wording of the question is as follows:

How large do you think is the probability that the total net income of your household in the next twelve months will be below level$_k$ *? Please give a number between 0 and 100.*

The answers to these questions will be denoted by PRO_1, ..., PRO_4, and correspond to values of the subjective distribution function of the next year's household income.

The first difference between our data and the data from the Survey of Economic Expectations (SEE) used by DM97 is that the levels to which the questions in our data refer are evenly spread over the range of possible realizations of next year's household income, while the levels in the SEE questions are taken from a given sequence. Given the validity of the lowest and highest possible realiza-

[2]The data set also contains information on other household members, but here we focus on the heads of the households.

[3]Evenly spread means that the level in question k ($k = 1, ..., 4$) is equal to: lowest possible income + $0.2k$ (highest possible income - lowest possible income).

tions, there will be no anchoring effect present in our data.[4] Given the midpoint between the lowest and highest possible income, DM97 select four values from a predetermined sequence of income thresholds in such a way that two thresholds are below and two thresholds are above the midpoint. This way of selecting thresholds avoids some anchoring problems, although it does not remove them completely. Respondents who are quite uncertain about their household income will see reasonable values for the thresholds, but if the head of the household is certain about the household income in the next twelve months, he will face rather low and high values for the thresholds, which might, in turn, induce him to spread his subjective density more widely.

The second difference between our data and the data from the SEE is that in the SEE, if a respondent gave an answer that was incompatible with the previous ones, this inconsistency was mentioned to the respondent. A new answer was then given. This way of questioning results in a higher fraction of valid answers, and will be pursued in the next wave of the CSS. For the current wave we will have to ignore the respondents who provided an inconsistent sequence of probabilities.

Unfortunately, the set of questions on income uncertainty is only presented to individuals who answered 'yes' to the question '*Do you know, APPROXIMATELY, how much the NET INCOME of your household would amount to over 1994?*' In our sample, 769 (35%) of the heads of the households state that they do not know this. These respondents are mainly the lower educated and females. The remaining 1,420 respondents all answered the question about the household's lowest and highest possible income for the next year. After deleting households with extremely low values for their income and a few households giving a higher value for the lowest possible income than for the highest possible income, 1,333 households remain with observed lowest and highest possible income levels for the next twelve months.

Following the questions on lowest and highest possible incomes, the heads of

[4] Anchoring means that a respondent adjusts his beliefs to the questions that are asked. If a respondent believes that the household income will never be below, say, Dfl. 40,000, he may still be induced to give positive probabilities to outcomes below this value. This can be the case if, for example, the levels that are referred to are all below this level of Dfl. 40,000. The reasoning of the respondent in this case is that his beliefs might be wrong (since the researcher seems to be interested in these low outcomes). The respondent might think that the values mentioned in the questions are objectively reasonable.

the households are asked to evaluate the probability with which their household income will fall below a certain level. Four questions of this type are asked, and, in theory, the probabilities provided by the respondents should result in a non-decreasing sequence of answers. This is not true for 198 of the heads of the households, while three heads of households do not answer the questions.[5] Due to some missing values for other household characteristics, our final sample consists of 1,122 individuals for which we observe all the information we need and for whom we can construct a subjective distribution for the next year's income.

The number of observations we finally use in the analysis is rather low compared to the number of observations in the original sample. This could be due to the fact that we are dealing with subjective data and respondents may have difficulties or may show more resistance in answering this type of questions. The major reason for dropping out in our case, however, is caused by the question concerning realized income in the previous year, which is objectively measurable.

In Table 3.1 we present some descriptive statistics for the representative panel. In the calculation of these statistics we use weights to correct for the drop out of mainly the low educated and females.[6]

The numbers in Table 3.1 indicate that there is substantial variation in the respondents' answers to PRO_1, ..., PRO_4. Looking at the average or median answers to PRO_1 until PRO_4, we see that the subjective distribution of the next year's income is skewed to the left. Especially the top part of the interval [lowest income, highest income] contains a large probability mass. A table for the high-income panel shows similar answers to the probability questions, whereas the stated possible incomes are higher for the high-income panel, as could be expected. This suggests that if we condition on income, we don not need to distinguish between the two parts of the panel.

3.3 Measuring subjective income uncertainty

We use as a measure of income uncertainty the ratio of the *interquartile range* (IQR) and the *median* (MED) of the subjective distribution of the next year's

[5] The individuals that give answers that are incompatible with previous answers are mainly employed and lower educated heads of households.

[6] The weights are constructed in such a way that the fractions of the low educated and of females in the final sample correspond to the fractions in the original representative panel.

Table 3.1: Descriptive statistics for the answers to the quantitative questions for the representative part of the panel. Income is measured in Dutch guilders (1 Dfl. $\approx$ 0.5 US Dollar).

	Lowest Income	Highest Income	PRO_1	PRO_2	PRO_3	PRO_4
Minimum	3,000	5,000	0	0	0	0
1st Quartile	26,400	31,668	0	10	20	40
Median	40,000	45,000	10	25	50	70
3rd Quartile	51,000	60,000	30	50	70	89
Maximum	185,000	358,000	100	100	100	100
Mean	39,261	45,408	20.2	33.1	47.4	60.4
Std. Dev.	20,222	24,874	24.8	28.2	30.3	31.0

household income. The variation in income is thus measured relative to the location of the income distribution. A Dfl. 5,000 increase is a large change in income for a household with a low income, while it is only of minor importance for a household with a high income. A 10% increase in income, however, is likely to be significant for both a high-income and a low-income household.

We explicitly use the information on the reported lowest and highest possible incomes by putting all the probability mass on the reported interval. Furthermore, we assume that the density of the subjective income distribution is simply (piecewise) uniform over the intervals. We obtain an estimate of the cumulative distribution function by interpolation between the known points 0, $PRO_1, \ldots, PRO_4$, and 100. Given this estimated distribution, it is straightforward to compute the IQR and MED as measures of spread and location.

It would be interesting to know what the relationship is between the expected level of income and subjective income uncertainty. (The rank correlation between the IQR and MED is 0.43 and highly significant.) In case IQR is proportional to MED, the relative income uncertainty (IQR/MED) is constant (with respect to MED), which implies that households that expect a higher income next year do not perceive a greater or smaller *relative* uncertainty than other households. Using our data, we (nonparametrically) regress the quotient IQR/MED on MED.

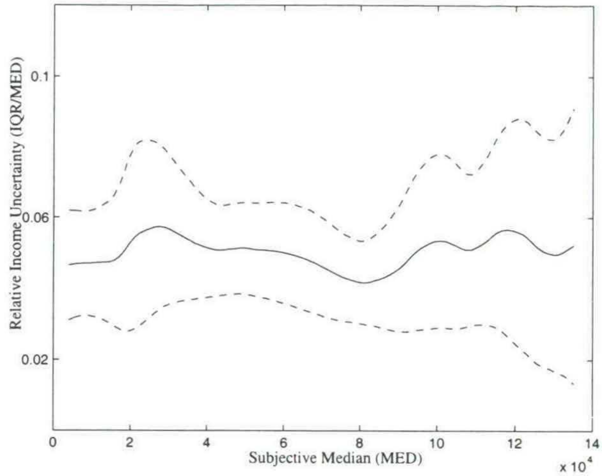

Figure 3.1: Nonparametric regression of relative subjective income uncertainty (IQR/MED) on the subjective median of future income (MED). The dashed lines are 95% uniform confidence intervals.

The result is presented in Figure 3.1. Together with the estimated functional relationship between IQR/MED and MED, we present 95% uniform confidence bounds.[7]

Figure 3.1 shows that the median of the subjective income distribution has no significant effect on relative income uncertainty as perceived by the head of the household. This result supports the approach taken in the studies by Skinner (1988), Zeldes (1989), and Carroll (1992), where the household's subjective IQR is assumed to be proportional to the median.

3.4 Prediction of the subjective measure of income uncertainty

The previous section showed that our measure of income uncertainty does not vary systematically with the level of expected income. This analysis, however,

[7]We use the quartic kernel and a bandwidth equal to $1.5 * 10^4$. For details on nonparametric regression, see e.g. Härdle and Linton (1994).

used only MED as an explanatory variable. In this section we examine how our measure of income uncertainty varies with some other household characteristics. A (possible) correlation could yield useful information. First, if a relationship exists, this information might be useful for studies in which no subjective data are available, since our analysis then shows how one could proxy income uncertainty for each household. Second, if we find no correlation at all, this may cast doubt on our measure of income uncertainty based on the subjective data, especially in cases where a relationship between income uncertainty and household characteristics is plausible. Before we discuss the results for income uncertainty, we will examine the location of the subjective income distribution.

The location of the subjective income distribution

We estimate a model for the median of the subjective income distribution (as a measure of location) similar to the specification used by DM97. We allow for a more flexible age pattern than DM97 and we also distinguish between respondent and spouse with respect to labor-force participation.[8] The exact definitions of the explanatory variables can be found in the appendix to this chapter. We use LAD estimation to make our estimates robust to outliers, and bootstrapping to calculate the asymptotic covariance matrix. The reported standard errors are corrected for potential heteroskedasticity. Table 3.2 presents the estimation results.

The first column in Table 3.2 shows that household income in the past twelve months is a dominant predictor for expected household income in the next twelve months. A striking result is that the estimated coefficient is almost the same as found by DM97. The best linear prediction of the location measure of the subjective income distribution increases by 834 Dutch guilders with every one thousand guilders increase of past household income. There is a clear pattern for the education dummies, indicating that the higher educated expect a higher income (*ceteris paribus*), but none of dummies is significant.

The first column of Table 3.2 also shows that differences exist between the head of the household and his/her partner in the effect of labor-market status

[8]We tested for the presence of a sample selection bias. The hypothesis that there was no sample selection bias could not be rejected.

Table 3.2: Estimation results for the median of the subjective income distribution. Standard errors in parentheses.

DEPENDENT VARIABLE: MEDIAN (in thousands of Dfl.)				
	without interactions		with interactions	
Constant	7.58	(4.3)	10.7	(4.3)
PastInc	0.834	(0.021)	0.813	(0.036)
PastInc×DumWork			0.101	(0.045)
PastInc×DumWorkP			-0.115	(0.042)
DumWork	2.34	(0.74)	-2.11	(1.7)
DumWorkP	-1.84	(0.82)	3.44	(2.0)
DumUnem	-2.08	(0.79)	-1.79	(1.0)
DumUnemP	-0.277	(1.9)	-0.791	(1.5)
DumFemale	-0.969	(0.59)	-1.31	(0.73)
DumPartner	1.53	(0.76)	1.00	(0.87)
Age/10	-1.36	(1.4)	-1.79	(1.6)
$Age^2/100$	0.135	(0.13)	0.162	(0.15)
DumEdu2	0.772	(0.80)	0.210	(1.1)
DumEdu3	0.431	(0.89)	0.122	(1.2)
DumEdu4	1.58	(1.1)	1.54	(1.2)
DumEdu5	2.34	(1.2)	1.89	(1.7)
DumStartW	0.994	(1.9)	0.232	(1.7)
DumStopW	-4.57	(2.0)	-5.10	(2.1)
Average Abs. Dev	15.8		15.7	

on expected income. DM97 consider only the aggregate effect of labor force participation by respondent and spouse. They find no significant influence. Here we see, for example, that if the head of the household has a job, and a partner is present in the household, the difference in the median between a working and non-working partner is significant and almost Dfl. 2,000 (*ceteris paribus*). The negative sign of the variable DumWorkP might be explained by the type of jobs (and the corresponding salary) partners have. This is best illustrated when we allow household income to interact with the employment dummies for head of the household and partner. The resulting estimates are presented in the second column of Table 3.2. When we consider a household in which the head of the household has a paid job and the partner does not have a paid job, the coefficient on household income equals 0.914. For a household in which both the head of the household and the partner have a paid job, this coefficient is equal to 0.798. This suggests that the previous year's household income is less dominant in predicting the next year's household income when the partner has a paid job. Note that these results are conditional on whether or not the head of the household expects a household member to stop working. This expectation exerts a strong negative effect. The effect of a member of the household who is expected to start working is smaller and insignificant. The estimates for the parameters that are not related to labor market status are similar in the first and second column, so we will not discuss them separately.

Income uncertainty

As we mentioned before, the ratio of IQR to MED will be used as our measure of income uncertainty. This measure looks at income changes relative to the level of income as measured by the median of the subjective distribution. We use the same model as in the analysis of the median. Instead of using the dummy variables corresponding to start/stop working (which proved to be insignificant), we incorporate a number of variables referring to expectations about income changes in the past and future. The variable PrevΔInc denotes the subjective change in household income over the last twelve months, and the variable ExpΔInc refers to the expected income change in the next twelve months (both variables are in percentage terms). The estimation results are presented in Table 3.3.

The results in the first column of Table 3.3 reveal that the household income over the past twelve months has a significant positive effect on the relative income uncertainty, although we could not reject proportionality between IQR and MED (see Figure 3.1). Note, however, that when the household income is (*ceteris paribus*) Dfl. 10,000 higher, the best linear prediction of the relative income uncertainty increases by less than 0.2%.[9] The effect is thus rather small.

[9] We also included a quadratic term in past income, but this did not change the results, with

Table 3.3: Estimation results for subjective income uncertainty. Standard errors in parentheses.

DEPENDENT VARIABLE: 100*(IQR/MED)				
Constant	10.9	(2.0)	9.07	(2.6)
PastInc	0.0145	(0.0065)	0.0128	(0.0048)
DumWork	0.738	(0.21)	0.716	(0.40)
DumWorkP	-0.0852	(0.32)	0.0804	(0.40)
DumUnem	1.27	(0.65)	1.08	(0.61)
DumUnemP	1.78	(0.37)	1.45	(0.57)
DumFemale	-0.786	(0.35)	-0.731	(0.23)
DumPartner	-0.450	(0.42)	-0.451	(0.32)
Age/10	-3.50	(0.62)	-2.91	(0.82)
$\text{Age}^2/100$	0.280	(0.052)	0.235	(0.068)
DumEdu2	0.525	(0.32)	0.456	(0.27)
DumEdu3	0.603	(0.40)	0.559	(0.38)
DumEdu4	0.177	(0.26)	0.162	(0.29)
DumEdu5	0.713	(0.43)	0.651	(0.41)
$\text{Prev}\Delta\text{Inc}$			0.0222	(0.040)
$\lvert\text{Prev}\Delta\text{Inc}\rvert$			0.0321	(0.035)
$\text{Exp}\Delta\text{Inc}$			0.0595	(0.047)
$\lvert\text{Exp}\Delta\text{Inc}\rvert$			0.0984	(0.035)
Average Abs. Dev.	4.09		4.04	

When we look at the labor market status variables for head of household and partner, we see that if the partner has a job, this does not influence relative income uncertainty, whereas the fact that the head of the household has a job increases relative income uncertainty by almost one percentage point. The unemployment dummies for head of household and partner are of the same order of magnitude and are both significant. Females perceive less income uncertainty than males. We have also included a quadratic age pattern, in which income uncertainty reaches its minimum at the age of retirement. No clear pattern can be seen for

the quadratic term being insignificant.

the different educational levels, but a test on the joint significance of the dummy variables, corresponding to the level of education, indicates that differences do exist between educational levels (the significance probability equals 0.03).

When we include a number of characteristics of past and expected income changes, we obtain the results presented in the second column of Table 3.3. It turns out that only the absolute value of the expected income change, $|\text{Exp}\Delta\text{Inc}|$, has a significant influence on income uncertainty: the larger the expected change, the more uncertain the head of the household will be about future income. We have included both the expected income change and its absolute value to see whether an expected increase in household income has a different effect from an expected decrease in household income. This, however, makes no difference. Also, past income changes have no significant effect. The effects of the other variables are the same as in the first column of Table 3.3. Only the variable DumUnem is no longer significant.

3.5 An international comparison

This section compares income uncertainty in the Netherlands with income uncertainty in Italy and the US. We do this by comparing the coefficients of variation of the subjective income distributions. For Italy, we use the results that are reported by Guiso et al. (1992). They use the biennial survey of the Bank of Italy [the Survey of Household Income and Wealth (SHIW)]. The SHIW elicits the subjective probability distributions for the growth rate of nominal labor earnings and pensions and for the rate of inflation over the next twelve months.[10] For the distribution of perceived income uncertainty in the US, we use the results of DM97.

[10]The exact wording of the SHIW question on the subjective probability distribution is: *We are interested in knowing your opinion about labor earnings or pensions twelve months from now. Suppose that you have 100 points to be distributed between these intervals* (a table is shown to the person interviewed). *Are there intervals which you definitely exclude? Assign zero points to these intervals. How many points do you assign to each of the remaining intervals?* For this, as well as a similar question on inflation uncertainty, the intervals of the table shown to the person interviewed are: >25, 20-25, 15-20, 13-15, 10-13, 8-10, 7-8, 6-7, 5-6, 3-5, 0-3, <0 percent. If it is less than zero, the person is asked: *How much less than zero? How many points would you like to assign to this class?* For further details on the Italian SHIW, see Guiso et al. (1992).

The set of questions used by DM97 is similar to ours, but the estimation strategy is different. DM97 estimate IQR and MED from fitting a lognormal distribution to the questions for each of the levels. They do not explicitly use the information on the highest and lowest possible incomes. For each individual they define:

$$(\text{MED}^*, \text{IQR}^*) = \arg\min_{\text{MED,IQR}} \Sigma_{k=1}^{4} \left(\frac{\text{PRO}_k}{100} - LN(\text{level}_k; \text{MED,IQR}) \right)^2$$

Note that this is not the usual parameterization of the lognormal distribution, but that there exists a one-to-one relationship between (MED, IQR) and (μ, σ^2). Unfortunately, this method does not work for households with at least three times a value of zero or one. The best-fitting distribution in that case is a degenerate distribution with all mass at level$_k$, for which the corresponding PRO$_k$ is unequal to zero or one. Another problem with this method relates to the fact that a lognormal distribution has a positive density for each positive income level and will thus automatically have a positive probability mass outside the interval [lowest income, highest income]. Comparing the fitted distribution with the levels of the lowest and the highest possible income, we find that the probability mass outside the interval may be substantial. To give an indication, in our case (when we apply the same method as DM97) for almost 30% of all the respondents with a non-degenerate subjective distribution, more than half of the total probability mass lies outside the interval. Moreover, for approximately 20% of all the respondents with a non-degenerate subjective distribution, the median lies outside the interval. This seems unrealistic. The fact that the lognormal distribution gives a good approximation of the distribution of household incomes over the population does not imply that this is also the case for (subjective) income distributions on the household level.

Table 3.4 presents the distribution within the population of perceived income uncertainty for the three countries. The first three columns reveal that the income uncertainty in The Netherlands, as measured by the coefficient of variation, lies between the income uncertainty in Italy and the income uncertainty in the US. This result suggests that Dutch households perceive more income uncertainty than Italian households, but that households in the US perceive more income uncertainty than households in The Netherlands. For better comparability between the US and the Netherlands, we also report (in the last column) the estimates

Table 3.4: Relative frequency distributions of the variation coefficient of future income.

	Dutch VSB panel	Italian SHIW	US SEE	Dutch VSB panel
	Interpol.			Lognormal
$\sigma/\mu = 0.000$	0.18	0.34	0.20	0.28
$\sigma/\mu \leq 0.005$	0.28	0.44	0.20	0.30
$\sigma/\mu \leq 0.015$	0.44	0.70	0.20	0.36
$\sigma/\mu \leq 0.025$	0.58	0.88	0.20	0.47
$\sigma/\mu \leq 0.035$	0.66	0.94	0.21	0.55
$\sigma/\mu \leq 0.045$	0.73	0.99	0.22	0.62
$\sigma/\mu \leq 0.065$	0.82	1.00	0.24	0.71
$\sigma/\mu \leq 0.100$	0.91	1.00	0.34	0.81
$\sigma/\mu \leq 0.150$	0.95	1.00	0.44	0.89
$\sigma/\mu \leq 0.200$	0.97	1.00	0.53	0.92
$\sigma/\mu \leq 0.300$	0.99	1.00	0.70	0.96
$\sigma/\mu \leq 0.400$	1.00	1.00	0.78	0.98
$\sigma/\mu \leq 0.500$	1.00	1.00	0.85	0.98
$\sigma/\mu \leq 1.000$	1.00	1.00	0.94	0.99
$\sigma/\mu \leq 2.000$	1.00	1.00	0.98	1.00
$\sigma/\mu \leq 5.000$	1.00	1.00	0.99	1.00
# observations	1,122	2,909	437	982

Note: For the Dutch VSB panel, the estimation procedure for the unknown parameter vector in case of the lognormal distribution does not converge when the respondent gave the same answer to all $PRO_1, \ldots, PRO_4$. For this reason we could not use all the observations.

using the estimation strategy of DM97. As expected, we have higher levels of income uncertainty, due to the large probability mass attributed outside the interval [lowest income, highest income]. To see whether the distribution of σ/μ in the US is really different from the one in the Netherlands, we performed a χ^2-test. The resulting test statistic is equal to 408, exceeding the critical value of 26.3. It should be noted that part of this result might be caused by different survey methods. However, the type of questioning and the estimation procedure in the SEE and in the CSS are similar. In that respect, the US and the Dutch results are comparable. It therefore seems safe to conclude that perceived income uncertainty is smaller in The Netherlands than it is in the US.

3.6 Conclusions

We have analyzed subjective data on income uncertainty using the 1995 wave of the Dutch CentER Saving Survey. In the analysis, we have used answers to questions that elicit the subjective distribution of the next year's household income.

We have used, as a measure of income uncertainty, the ratio of the interquartile range and the median of the subjective distribution of the next year's household income. The median itself is used as a location measure. We find that the household income over the past twelve months is a dominant predictor for future income. However, the previous year's household income is less dominant in predicting next year's household income when the partner of the head of the household has a paid job.

Income uncertainty is higher when household income in the recent past is higher, although the effect is rather small. With respect to the labor-market status of the partner of the head of the household, we find that if the partner is unemployed and searching for a job, the head of the household reports a higher uncertainty about future income. The effect of expected changes is also significant: the larger the expected change in future income, the higher the reported uncertainty about next year's household income will be. Perceived income uncertainty decreases with age until retirement. Comparing our measure of income uncertainty with corresponding studies conducted in the US and Italy, we find that perceived income uncertainty in the US is larger than in the two European countries.

The results from our analysis suggest that it is worthwhile to use subjective data. This type of data provides useful information and can be used to measure income uncertainty, which is an important aspect in household decision making. A next step would be to explicitly incorporate subjective data on income uncertainty in models explaining household behavior.

3.A Description of variables

Variable	Description
MED	Median; derived from the interpolated subjective expected income distribution.
IQR	Interquartile range; derived from the interpolated subjective expected income distribution.
PastInc	Midpoint of income bracket that contained the household's income in the past twelve months according to the head of household (eleven brackets are used). The variable is measured in thousands of Dutch guilders.
DumWork	Dummy variable: 1 if the head of household has a paid job.
DumWorkP	Dummy variable: 1 if the partner has a paid job.
DumUnem	Dummy variable: 1 if the head of household is unemployed and searching for a job.
DumUnemP	Dummy variable: 1 if the partner is unemployed and searching for a job.
DumFemale	Dummy variable: 1 if the head of household is female.
DumPartner	Dummy variable: 1 if there is a partner present in the household.
Age	Age of the head of household.
DumEdu1..5	Dummy variables for education levels in increasing level of education: DumEdu1: primary education DumEdu2: lower secondary education DumEdu3: higher secondary and intermediate vocational education DumEdu4: higher vocational and pre-university education DumEdu5: university education Reference group is DumEdu1.

Variable	Description
DumStartW	Dummy variable: 1 if the head of household expects that household income in the next twelve months will be influenced by the fact that *a* member of the household who is currently not employed will start working.
DumStopW	Dummy variable: 1 if the head of household expects that household income in the next twelve months will be influenced by the fact that a member of the household who is currently employed will stop working.
PrevΔInc	Previous change in income in the past twelve months. The variable is measured in percentage terms.
ExpΔInc	Expected change in income in the next twelve months. The variable is measured in percentage terms.

Chapter 4

Estimating risk attitudes using lotteries; a large sample approach

Attitudes towards risk play a major role in many economic decisions. In empirical studies one quite often assumes that attitudes towards risk do not vary across individuals. This paper questions this assumption and analyses which factors influence an individual's risk attitude. Based on questions about lotteries in a large household survey we semiparametrically estimate an index for risk aversion. We only make weak assumptions about the underlying decision process and our estimation method allows for generalizations of expected utility. We also estimate a structural model based on Cumulative Prospect Theory. The estimated value function depends on gender, age, income and wealth. Expected utility is strongly rejected and the probability weighting function varies significantly with age, income, and wealth of the individual.

4.1 Introduction

Attitudes towards risk are important in many economic decisions. In empirical studies of economic behavior, however, direct information about attitudes towards risk is hardly ever available. In this chapter a large Dutch household survey is used that contains both direct information on respondents' attitudes towards risk and a lot of background information on the respondents. We use these data to investigate whether attitudes towards risk vary with other observed characteristics of the respondents, such as age and income. Whether and how an individual's attitude towards risk varies with observed characteristics can be helpful in empirical studies where this type of information is missing, while the background characteristics are observed.

Our inference on attitudes towards risk is based upon a set of eight questions on lotteries that are present in the data. In five of these questions the respondents make a choice between two lotteries. The remaining three questions are probability equivalence questions. Here the respondents have to state the minimum probability of winning a given prize, which would make them indifferent between such a lottery and a given amount of money. Both types of questions have a risky (high variance) and a safe (low or zero variance) option. We use these data to distinguish between more and less risk averse individuals.

To see how an individual's attitude towards risk relates to other observed characteristics we start with a very general semiparametric model. We do not use any economic or psychological theory, but only impose a single index restriction and a monotonicity condition, such that the index represents the respondent's risk aversion. The estimation results show a significant relationship between risk aversion and age, gender, education level, and income.

The semiparametric model is too general to permit a clear cut interpretation of the consequences of differences in attitudes towards risk. Therefore, we set up a structural model for the individual's decision process. Expected utility theory seems a good starting point in analyzing decisions under risk. However, within the experimental psychology literature considerable evidence is reported against the validity of expected utility when individuals answer questions on lotteries, see, for example, Kahneman, Slovic and Tversky (1982), or Machina (1987). Instead of the expected utility framework we will use Cumulative Prospect Theory as developed by Kahneman and Tversky (1979) and Tversky and Kahneman (1992). Expected utility can be seen as a special case of Cumulative Prospect Theory. The parametric approach used here enables us to use a larger set of explanatory variables. We find a large effect of wealth on risk aversion and also systematic variation of the probability weighting function with observed characteristics. Focussing on the same set of explanatory variables as in the semiparametric model it turns out that the semiparametrically estimated index is similar to the index for the value function. This seems to be the result of a small influence of the variation in the decision weighting function on the outcomes. The estimates from the parametric model thus give us an interpretation of the semiparametric estimation results.

The approach we take is possible because the data contain the questions related to risk attitudes as well as many background variables for almost 4,000 individuals. This contrasts with the datasets that have been used until now to derive measures for individuals' attitudes towards risk. In the experimental psychology and economics literature the datasets are, in general, rather small, consisting of no more than 200 individuals, and contain hardly any background information. The respondents in these studies are also very often students and the results may not be representative for the population of interest. The presence of small datasets is illustrated by the fact that Harless and Camerer (1994) merged a total of 23 datasets to obtain nearly 8,000 choices, where at least 3 choices are made by each individual. Our results are based on more than 20,000 choices. In the economics literature an indirect measure of risk aversion is sometimes derived from observed behavior, but the results obtained with this approach are quite sensitive to many real life aspects that are unrelated to risk aversion. Examples of this line of research are Pålsson (1996), who estimated risk aversion from portfolio choices, and Guiso et al. (1992), who derived a measure of risk aversion from savings data. A final branch in the literature uses large datasets from, for instance, TV shows or bets on horse races, but these datasets address very specific populations and contain no background information on the individuals making the decisions (see, for example, Beetsma and Schotman (1997) and Jullien and Salanie (1997)). An exception is Hartog et al. (1997), who used a dataset containing almost 2,000 individuals and a lot of background information, but in which direct information on risk attitudes is provided by only a single question.

The questions that are asked in our survey are purely hypothetical and no real incentives are provided. This can be seen as a drawback of the method of data collection. Fortunately, however, there is evidence (see, for example, Beattie and Loomes (1997) and Camerer and Hogarth (1999)) that for simple choice problems respondents do not need real incentives to reveal their preferences. To show that our data contains relevant information on decision making under risk, we confront the answers to the hypothetical questions with a question on stock ownership and a self-reported measure of risk attitude. We find strong relationships in the expected directions, indicating that the answers provided by the respondents reveal information about their true preferences in spite of the lack of real incentives. We also use the panel character of the data to check whether the answers to the questions are related to answers to similar questions asked a few months later, which they are.

Information on how risk aversion varies across individuals can be useful in predicting savings or stock holdings of an individual or household, since risk aversion plays an important role in these decisions. However, the existing empirical literature on modelling savings and portfolio choices focuses mainly on the effect of income risk and makes restrictive assumptions about the individuals' attitudes towards risk. For example, Lusardi (1997) estimated a single coefficient for risk aversion, which is the same for all individuals, while Guiso et al. (1992) allow risk aversion to depend only on lifetime resources. The present paper shows that attitudes towards risk also vary with other individual characteristics. Our analysis indicates which variables could be used to model attitudes towards risk in empirical applications, where no direct information on risk attitudes is available.

The remainder of this chapter is structured as follows. We start with a detailed description of the data in Section 4.2. Here we also demonstrate that the data provide information on true preferences. Section 4.3 presents the reduced form model and the semiparametric estimation techniques we will use, and Section 4.4 presents the semiparametric estimation results. Section 4.5 discusses the individual's decision making process, where we pay special attention to Cumulative Prospect Theory. Section 4.6 presents the structural model based on Cumulative Prospect Theory and its estimation results. Section 4.7 concludes.

4.2 Data

The data come from the first wave of the CentER Savings Survey (CSS), drawn in 1993, and consist of 2780 households, divided into two panels. One panel is designed to be representative of the Dutch population, the other panel is a random sample of the households in the upper 10% of the income distribution in The Netherlands. The CSS is a rich source of data, including information on household composition, income, assets and psychological concepts. A detailed description of the data can be found in Nyhus (1996).

One of the reasons why this panel contains so much information is that all participating households have been provided with a personal computer and answer the survey questions directly on their PC; no personal interviews are held. The fact that respondents answer the questions on a PC has the advantage that there is no interviewer present, who could possibly influence the answers. If the respondents have questions, they can call a helpdesk. There is, however, one problem when one performs experiments using the panel. It is impossible to have real incentives paid to the participants. Performing a laboratory experiment could be a good alternative. However, since our interest is in the variation of risk attitudes with other observed characteristics, performing an experiment is only a fruitful way to pursue if we have access to a heterogeneous sample of participants. Unfortunately, this is very difficult to realize. The main reason for using the CSS is that it provides access to a large and very heterogeneous sample of respondents. The fact that part of the panel is also representative of the population, makes it even more interesting, since this allows us to derive characteristics of the distribution of risk attitudes in the population. This is crucial if the results are to be used for economic policy analysis on an aggregate level.

The respondents do not have monetary incentives when answering the questions, as is often the case in experiments. Fortunately, there is evidence indicating that there is no difference in response for respondents with and without real payments, at least in the case of very simple problems such as lotteries with only two outcomes. Beattie and Loomes (1997) designed an experiment to investigate the relevance of real incentives in decision problems and concluded that '*in simple pairwise choices, incentives appear to make very little difference to performance.*' Further evidence is presented by, among others, Grether and Plott (1979) and Conlisk (1989) and is surveyed in Camerer (1995). Camerer and Hogarth (1999) presents a theory describing when payments can be expected to make a large difference and when not. The main conclusion is that payments increase the effort that is made by the respondent. This can be highly relevant for complex or tedious tasks, but our respondents are only presented with a short questionnaire on lotteries, that is completely new to them. It does not seem likely that our respondents are bored or disinterested, so the need for increasing their effort by monetary incentives is only small.

At the end of this section we will check whether the answers are informative about risk attitudes by comparing them with other objective and subjective measures of risk aversion. It turns out that the questions are significantly correlated with the other measures of risk aversion, indicating that the respondents have truthfully revealed information about their preferences regarding risk. Furthermore, we find strong and significant correlations between the answers and similar questions asked a few months later.

Our analysis draws heavily upon a set of questions on lotteries that are contained in the psychological questionnaire. The total numbers of households in the representative and high income panel answering the relevant psychological questionnaire are 1463 and 783, with total numbers of individual respondents of 2297 and 1652, respectively. The set of questions on lotteries consists of two types of questions (see Appendix 4.A for the precise wording of the questions):

1. The first type of questions deals with choices between two lotteries. Each time the respondent is offered two lotteries, each one with two possible outcomes with given probabilities,[1] and the respondents have to state their preferred lottery. It is mentioned that there do not exist right or wrong answers to these questions. We refer to these questions as choice questions.

   Five questions of this type are asked with varying outcomes and probabilities.

2. The second type of questions deals with the imaginary situation where a certain amount of money has been won and the individual has the opportunity to buy a lottery ticket with this money. This lottery ticket has a single prize of Dfl 20,000[2] and the question is how large the probability of winning this Dfl 20,000 has to be at least, to make the respondent willing to exchange the money for the lottery ticket. The amount of money that is exchanged for the lottery ticket varies over the questions. We refer to these questions as probability equivalence questions.

   Three questions of this type are asked.

The answers to the questions of the first type will be referred to by $CH^1, CH^2, \ldots, CH^5$ and are summarized in Table 4.1. We call the low variance lottery the safest

[1] In one case one alternative is winning zero with probability one.

[2] Dfl 1 was approximately US$ 0.50 by the end of 1993

option and the high variance lottery the riskiest option. A value 1 corresponds to the choice of the risky option, while 0 indicates that the safe option is chosen. Individuals opting for the safe lottery are called more risk averse than individuals choosing the risky option.

The answers to the questions of the second type, the probability equivalence questions, will be referred to by PE^1, PE^2, and PE^3. The answers indicate the probability (in %) of winning the prize of Dfl 20,000 for which the individual is indifferent between the lottery and an amount of money for sure of, respectively, Dfl 200 (PE^1), Dfl 1,000 (PE^2), and Dfl 5,000 (PE^3). The variables range from 0% to 100%. A higher probability of winning the prize implies a more attractive lottery. A more risk averse individual will thus give higher answers. The fact that a higher probability of winning corresponds to a more attractive lottery also implies a logical consistency requirement that $PE^1 < PE^2 < PE^3$, if marginal utility of money is positive (more is better). Otherwise individuals would prefer a stochastically dominated alternative. By now it is well known that probability equivalence questions result in overestimation of the level of risk aversion, due to, for example, response mode bias. In the questions we analyze, individuals have to give up money to participate, which might strengthen this bias.

In total we have 3949 individuals in our sample if we use both the representative panel and the high income panel. In the final analysis we will condition upon income, so there will be no effect of the overrepresentation of high income households. Sample means and other unconditional statistics will be reported for the representative panel only, so the numbers we present are representative of the Dutch population. For 491 respondents we miss important demographic information such as age or education, but mostly individual income, leaving us with 3458 observations. Furthermore, there are 865 individuals giving the answer "Don't know" to at least one of the probability equivalence questions. Most of them did not answer any question. This might be caused by lack of interest in this type of questions, but it can also be the case that these questions are rather difficult (see Warneryd (1996) for a discussion of this problem). We do not use observations with one or more missing values to the probability equivalence questions. The sample we use for estimation consists of 2593 individuals for whom we observe both the answers to the questions on the lotteries and the individual characteristics we want to use in explaining the individuals risk attitudes. These include 237 respondents who gave an inconsistent set of answers, satisfying either $PE^1 > PE^2$, $PE^2 > PE^3$ or $PE^1 > PE^3$.

The fraction of respondents choosing the riskiest option in the choice questions are presented in Table 4.1. The table shows that the number of individuals

Table 4.1: Descriptive statistics for the choice questions, representative panel only.

	fraction choosing	Safest		Riskiest	
Question	riskiest lottery	μ	σ	μ	σ
CH^1 (1000;1) vs. (2000;0.5)	0.21	1000	0	1000	1000
CH^2 (30;1) vs. (45;0.8)	0.40	30	0	36	18
CH^3 (100;0.25) vs. (130;0.20)	0.49	25	42	26	52
CH^4 (3000;0.02) vs. (6000;0.01)	0.56	60	420	60	597
CH^5 (0;1) vs. (1500;0.5,-1000;0.5)	0.12	0	0	250	1250

Note: $(x;p)$ denotes the lottery paying x with probability p and zero otherwise, while $(x;p,y;q)$ denotes the lottery paying x with probability p and y with probability q.

choosing the riskiest lottery varies considerably across the questions. This is largely due to the difference in expected value, μ, between the two lotteries relative to the difference in risk, σ, taken. For CH^1 and CH^4, there is no reward for the extra risk taken, i.e., the expected value of the two lotteries is the same. Respondents choosing the riskiest option in one of these two questions show risk loving behavior. Note, however, that some non-expected utility theories are able to explain this behavior, even if the marginal utility of money is decreasing, which is equivalent with the regular concept of risk aversion under expected utility as it is defined by Pratt (1964) and Arrow (1965). Aspects of these theories that can be relevant are the certainty effect in CH^1 and CH^2. For CH^4 subproportionality can be important, while for CH^5 it is loss aversion.

The mean and median of the probability equivalence questions can be found in Table 4.2. The mean of the answers to PE^1 is a 39% chance of winning Dfl 20,000, while the median answer to this question is 40%. The other columns have to be read in a similar way. There is a clear pattern of increasing answers if we go from PE^1 to PE^3, but there is also substantial variation across respondents for each question as follows from the reported standard deviations.

Before using these data to explore the relationship between risk attitudes and

Table 4.2: Descriptive statistics for the probability equivalence questions

	PE^1	PE^2	PE^3
	(200;1) vs. (20,000;p)	(1,000;1) vs. (20,000;p)	(5,000;1) vs. (20,000;p)
Mean	39.3%	49.5%	64.4%
Median	40%	50%	70%
Std. Dev.	28.1%	28.5%	26.6%

observed characteristics, we want to verify that the respondents' answers to the questions reveal information about their true preferences. Whether or not a respondent owns risky assets such as stocks, could be informative about the respondents' true preferences, since here real incentives certainly are present. Table 4.3 shows some characteristics of the answers to the questions for the subsample of respondents that own risky assets and the subsample of respondents that do not own risky asset, which we defined as stocks, mutual funds, and options, but not bonds. 493 respondents own risky assets, while 2100 do not hold risky assets in their portfolio.

Table 4.3: Averages for respondents with and without risky assets in their portfolios. Standard errors in parentheses.

Question	Subsample owning risky assets	Subsample not owning risky assets
CH^1	0.755 (0.019)	0.776 (0.009)
CH^2	0.481 (0.023)	0.561 (0.011)
CH^3	0.471 (0.022)	0.498 (0.011)
CH^4	0.444 (0.022)	0.418 (0.011)
CH^5	0.878 (0.017)	0.879 (0.007)
PE^1	25.53 (1.101)	36.54 (0.618)
PE^2	35.22 (1.199)	46.67 (0.637)
PE^3	55.12 (1.243)	61.89 (0.613)

We report the fraction of the respondents choosing the safe option in the choice questions, $CH^1 - CH^5$. For each question, except for CH^4, the fraction of the respondents choosing the safe option is smaller for the group of respondents that own risky assets indicating that ownership of risky assets is related to lower levels of risk aversion as indicated by the answers to the choice questions. The difference is highly significant for CH^2, but insignificant for the other questions. For the probability equivalence questions, $PE^1 - PE^3$, we report the average answers for the two subsamples. The differences are large and highly significant. They clearly imply lower levels of risk aversion for the owners of risky assets compared to the respondents that do not hold risky assets in their portfolios.

Apart from the questions on lotteries the survey contains other questions relating to risk aversion and risk taking behavior. One example is a question where the respondents have to answer on a seven point scale, whether they agree or disagree with the following statement: '*I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns*'. We computed the correlation coefficients between the answer to this question and the answers to the lottery questions we want to use. Each of the correlation coefficients is positive, indicating that the respondents that are more risk averse, according to the questions we use, also think it is more important to have safe investments and guaranteed returns. Except for CH^4, all the correlations are highly significant.

A final measure of reliability of the data can be obtained from a comparison of the data we use with the answers to a similar set of questions that was asked in a new wave of the CSS, about three months later. In the second wave only one question, PE^2, was maintained in its original form. The amounts for sure in the two other probability equivalence questions were changed and the choice questions were not repeated at all. Table 4.4 presents correlation coefficients between the answers to the probability equivalence questions in the two questionnaires, based on 2068 individuals that answered both questionnaires. The correlation coefficients are positive and highly significant. The correlation coefficient of 0.54 in the middle of the table is the most important one, since this is the correlation between answers to the same question in the two questionnaires. This correlation is reasonably high, given the time between the two questionnaires.

Even though the respondents do not have monetary incentives when answering the questions, the results presented above show that the answers to the choice questions and the probability equivalence questions are related to actual behavior, such as stock ownership, but also to other subjective measures of risk aversion. From this we conclude that the answers to the questions are informative about the respondents' true preferences. The evidence is strongest for the more difficult

Table 4.4: Correlation coefficients for the data in the two questionnaires.

93 / 94	(200;1) vs. (20,000;p)	(1,000;1) vs. (20,000;p)	(5,000;1) vs. (20,000;p)
(100;1) vs. (20,000;p)	0.54	0.51	0.38
(1,000;1) vs. (20,000;p)	0.51	0.54	0.45
(10,000;1) vs. (20,000;p)	0.20	0.29	0.33

probability equivalence questions. One of the reasons for this could be that some of the choice questions deal with extreme lotteries that were designed to detect specific violations of expected utility, such as loss aversion for CH^5 and subproportionality for CH^4. In the next section we use both types of question for our analysis. In the analysis based on Cumulative Prospect Theory in Sections 4.5 and 4.6 we will only focus on the probability equivalence questions, which have the strongest relations with actual behavior.

4.3 A semiparametric model for risk attitudes

Many papers have estimated attitudes towards risk using specific functional forms to represent preferences, see, for example, Beetsma and Schotman (1997), Lattimore, Baker, and Witte (1992), and Tversky and Kahneman (1992). Exceptions are Abdellaoui (1998), Gonzalez and Wu (1999), and Wakker and Deneffe (1996).

In this section we will not specify any functional forms. For the choice questions we assume that $E\{1 - CH^q|x\} = P\{\text{safest choice is chosen in question } q|x\} = G^q(x'\beta^q)$, with x a vector of observed characteristics such as age and income. β^q is a parameter vector that has to be estimated. The function $G^q(.)$ is unknown, but assumed to be increasing. A higher value of $x'\beta^q$, the individual specific index, now implies a higher probability for the safe option being chosen and thus more risk aversion.

For the probability equivalence questions we make a similar assumption, which is that $E\{PE^q|x\} = F^q(x'\beta^q)$. x denotes a vector of observed characteristics and β^q a vector of parameters. The function $F^q(.)$ is not known, but assumed to be increasing. Higher values of $x'\beta^q$ imply, on average, a higher answer to the probability equivalence question. As was the case for the choice questions, a higher value of $x'\beta^q$ implies more risk aversion. Therefore we will refer to the index as a measure of risk aversion.

One of the interesting questions is whether the indices for each of the questions are the same, which is something that is not assumed a priori. When we present the estimation results, we will also present the results of some tests on equivalence of the indices. If, for example, loss aversion is stronger for one group of individuals and small probabilities are more overweighted by another group, we could obtain different estimates for CH^4 and CH^5. This then indicates that we are not able to model the respondents' behavior towards all the questions with a single index.

With these assumptions the scale of β^q is not identified and we normalize the component of β^q that relates to the individual's gender, say the first component, such that $|\beta_1^q| = 1$. The sign of β_1^q and thus whether females are more or less risk averse than males is identified. These assumptions and some technical regularity conditions are sufficient to obtain a consistent estimator for β^q for each question separately, using the rank estimator proposed by Cavanagh and Sherman (1998), which is an extension of the maximum rank correlation estimator of Han (1987). One practical problem with this estimator is that the objective function does not behave very well with the data we have, which is due to properties of the objective function in small samples. We solved this problem by replacing the objective function with a smoothed version, following the idea of Horowitz (1992), which, under appropriate regularity assumptions, does not change the asymptotic properties of the estimator. For the probability equivalence questions we can use this initial estimator and the method proposed by Delecroix, Härdle, and Hristache (1997) to obtain asymptotic efficiency by a one step estimator based on the initial estimate. For the choice questions we use the same approach, where the efficient estimator is based on the ideas in Klein and Spady (1993). Technical details about the estimators are given in Appendix 4.B.

With the method described above, we obtain efficient estimates of β^q for each question. Since we are interested in a single measure of risk attitude per person and not in a measure of risk attitude per person for each question, we will test whether the estimated coefficients for the different questions are actually the same and thus whether there exists a unique measure of attitude towards risk for the questions we have. To combine the estimates from the different questions we use minimum distance (see Lee (1996), for example). Here we take into account the fact that we observe the same individual more than once and the estimates for the different questions are not independent.

4.4 Estimation results for the semiparametric model

This section presents the estimation results for the semiparametric model defined in the previous section. Tables 4.5 and 4.6 present the estimates for β and the corresponding standard errors for each of the questions separately. Although in theory we can use as many explanatory variables as we like, in practice this is not true. Given the weak assumptions we make, it is only possible to use a small set of explanatory variables, compared to the set of explanatory variables we can use with the parametric model that is presented in Section 4.6. As explanatory variables in our model we use a dummy variable for gender, age, the logarithm of income, and education level measured on a scale from 1 to 5. For some of the respondents we did not observe their personal income, or it was zero. For these respondents Log(Income) was set to zero and a dummy, Dinczero, was included to correct for this. Some descriptive statistics of the explanatory variables are given in Appendix 4.A.

Table 4.5: Estimation results for β for the choice questions. Standard errors in parentheses.

	CH^1	CH^2	CH^3
Female	1 (——)	1 (——)	1 (——)
Age	0.032 (0.004)	0.031 (0.003)	0.031 (0.004)
Log(Income)	-0.080 (0.046)	-0.364 (0.048)	-0.171 (0.043)
Education	0.088 (0.026)	-0.280 (0.030)	-0.088 (0.022)
Dinczero	-0.578 (0.477)	-3.530 (0.488)	-1.930 (0.449)

	CH^4	CH^5
Female	1 (——)	1 (——)
Age	0.214 (0.022)	0.031 (0.008)
Log(Income)	-1.127 (0.134)	0.125 (0.058)
Education	-0.272 (0.041)	0.063 (0.037)
Dinczero	-8.419 (1.056)	1.232 (0.551)

Table 4.6: Estimation results for β for the probability equivalence questions. Standard errors in parentheses.

	PE^1	PE^2	PE^3
Female	1 (——)	1 (——)	1 (——)
Age	0.029 (0.001)	0.031 (0.001)	0.032 (0.001)
Log(Income)	-0.423 (0.021)	-0.437 (0.022)	-0.450 (0.022)
Education	-0.446 (0.016)	-0.454 (0.017)	-0.463 (0.017)
Dinczero	-3.180 (0.190)	-3.274 (0.199)	-3.372 (0.203)

The estimates are all significant, except for the effect of income on CH^1 and the effect of education on CH^5. The estimates for the three probability equivalence questions are very similar, even though the estimates are computed completely independent from each other. Also the signs of the estimates for CH^2, CH^3, and CH^4 are the same. Similar results are also obtained using regression and probit models. From the estimates we see that females and old people are more risk averse, while individuals with a higher education level or a higher income are less risk averse. The estimate of the parameter for the dummy indicating that the individual has no observed personal income indicates that the level of risk aversion for such an individual is similar to the risk aversion of an individual with an average income. The extent to which a different value for the index results in different behavior will be discussed at the end of this section.

Table 4.7: Minimum distance estimates for β. Standard errors in parentheses.

	All questions	only PE questions
Female	1 (——)	1 (——)
Age	0.024 (0.001)	0.031 (0.001)
Log(Income)	-0.293 (0.007)	-0.436 (0.008)
Education	-0.321 (0.005)	-0.454 (0.006)
Dinczero	-2.160 (0.063)	-3.273 (0.070)

Since we are interested in a single measure of risk aversion, we combine the estimates for the questions using minimum distance with an optimal weighting matrix. The first column of Table 4.7 presents the resulting estimate for β using the choice and the probability equivalence questions jointly. However, when we test the hypothesis that the original estimates for the questions are estimates of the same β, this hypothesis is strongly rejected.[3] The correlation between the estimated indices, however, is high, ranging from 0.56 to 0.99. Looking at the questions, there is a large difference between the choice questions and the probability equivalence questions. The choice questions themselves also apply to different aspects of individual decision making, which were discussed when we presented the questions. When we test whether the estimates for β that we derived from the choice questions are the same, this hypothesis is again strongly rejected. For the probability equivalence questions we cannot reject the hypothesis that they are estimates for a unique β. The minimum distance estimate for β using only the probability equivalence questions is presented in the second column of Table 4.7. The hypothesis that the index for one of the choice questions was the same as the joint index for the probability equivalence questions was rejected for each of the choice questions. In the rest of this section we will refer to the index based on the probability equivalence questions as the index of risk aversion. We will denote this index with $x'\beta^{PE}$. The fact that the probability equivalence questions, in general, induce high levels of risk aversion has no consequences, since the index only represents an ordering of the respondents with respect to their level of risk aversion.

We now give a possible interpretation of the most important differences between the parameter estimates for the different questions. In general, we can say that the effect of education and income on the index is smaller in the choice questions than in the probability equivalence questions. The effect of age is similar for all the questions except for CH^4, where the effect is much stronger, even if we compare it with the other coefficients. This could indicate that subproportionality of the probability weighting function is less important for old people. Estimation results that are presented in Section 4.6 confirm this.

For CH^5 the estimated parameters for income and education in the index are different from the other questions. Since this question involves a loss, we can interpret the observed difference in the parameter estimate as being related to an index for loss aversion. Loss aversion means that losses have a larger disutility than gains of the same magnitude. For a detailed description of loss aversion and its possible causes see Kahneman et al. (1991). The difference between the

[3]The test is based on the scaled sum of squares of the differences between the original estimates and the minimum distance estimate and follows a χ^2 distribution.

estimate for CH^5 and the other estimates then implies that loss aversion is less decreasing with income and education level than an individual's risk attitude.

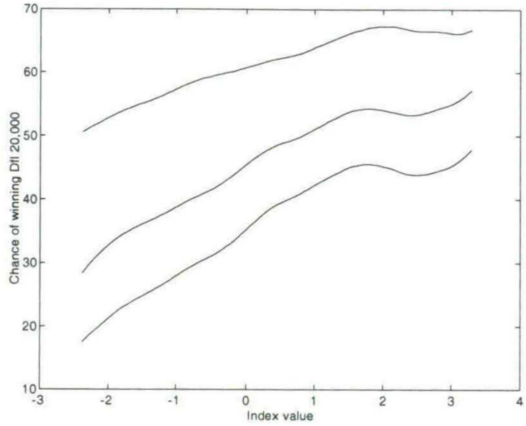

Figure 4.1: Estimated conditional expectation of PE^1, PE^2, and PE^3 as a function of the index.

We estimated our model under the assumption that the answers to the questions depend on the level of risk aversion and that the answers are increasing in risk aversion. In Figure 4.1 a plot is made of $E\{PE^q|x'\beta^{PE}\}$ for the three questions, where, as the consistency requirement indicates, the lowest line is for PE^1, the middle line for PE^2, and the highest line for PE^3. We do not include confidence bands in the figure, since they make the figure unreadable, but based on uniform confidence bands we can conclude that the monotonicity of neither of the three lines is rejected and that the three conditional expectations are significantly different from each other. An estimate of the density of the index value of the respondents in our sample is presented in Figure 4.2. Given the fact that the density of the index is well spread over the interval $[-2, 3]$, we can conclude from Figure 4.1 that there is substantial variation in the individual's risk attitudes in our sample. There is, however, also a lot of unexplained variation. A measure of fit[4] based on the usual R^2 measure obtains values of 0.023, 0.067, and 0.092 for

[4]We define the measure of fit as $1 - \frac{V\{PE_i^q - E\{PE_i^q|x_i'\beta^{PE}\}\}}{V\{PE_i^q\}}$. Here $PE_i^q - E\{PE_i^q|x_i'\beta^{PE}\}$ is the prediction error for respondent i.

PE^3, PE^2, and PE^1, respectively, indicating that we explain relatively more for the first two questions, PE^1 and PE^2.

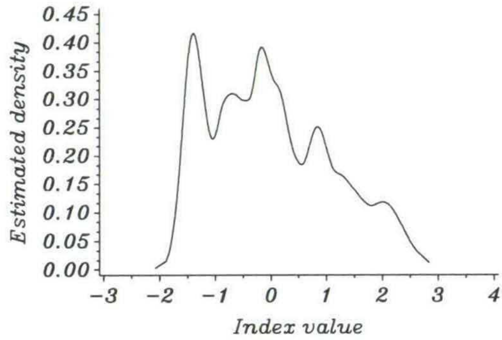

Figure 4.2: Estimated density for the index, $x'\beta^{PE}$.

Although we had to reject the hypothesis that we could use a single index to model all the questions, it can still be the case that the measure of attitude towards risk derived from the probability equivalence questions has some predictive power for the choice questions. If this is not the case, it might not make a lot of sense to pay attention to such a measure, since it could be too dependent on the form of the questions and might have hardly anything to say about a more general attitude towards risk. However, if we do find significant relationships between the answers to the choice questions and the index based on the probability equivalence questions, we can interpret the index as a general measure of risk aversion. To check whether the index also has some predictive power for the choice questions in the sense that a higher index for an individual is related to a higher probability of choosing the safest option we performed nonparametric regressions of the answers to the choice questions on the index derived from the probability equivalence questions. The results of these regressions are presented in Figure 4.3.

For each question the estimated conditional expectation tends to increase. We used uniform confidence bands to formally test the null hypothesis that the functions are flat horizontal lines. For CH^1 and CH^5 we are not able to reject this hypothesis. For the other three questions we could reject this hypothesis and the conditional expectation for each of these questions significantly depends on

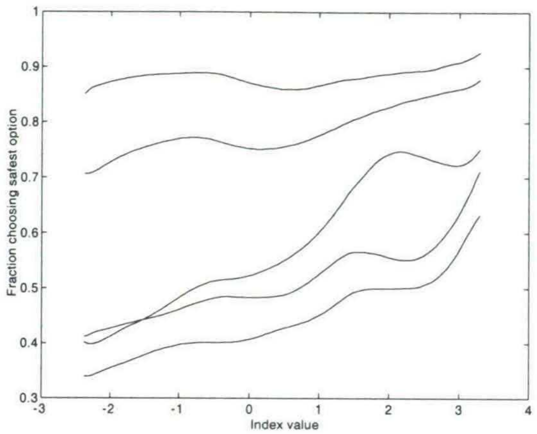

Figure 4.3: Estimated conditional expectation for the choice questions. From top to bottom we have CH^5, CH^1, CH^2, CH^3, and CH^4.

our measure of risk attitude. We can thus conclude that even though we could not model all the questions with a single index, we can still obtain an index that is related to all the questions and that can thus be interpreted as a general measure of risk aversion.

However, from the relationships that are depicted in Figures 4.1 and 4.3 we cannot conclude very much about the way the underlying decision process changes if the value of the index changes. The next section presents a structural model of the individual's decision making process, which will help us in interpreting the results discussed above.

4.5 A structural model for the individual's decision making process

In economics the basic tool to deal with decision making under uncertainty is the expected utility model. This means that preferences over probability distributions can be represented by an expected utility function $E\{u(x)\} \equiv \int_X u(x)\mathrm{d}F(x)$, where $u(x)$ is a utility function and the expectation is taken with respect to the probability distribution, F. Two well known measures of risk aversion are derived by Arrow (1965) and Pratt (1964). Let $u(x)$ be the utility function of an individual, then $-\frac{xu''(x)}{u'(x)}$ is a (local) measure of relative risk aversion, while $-\frac{u''(x)}{u'(x)}$ is a (local) measure of absolute risk aversion. These are the types of concepts we are interested in. However, a lot of systematic violations of expected utility maximizing behavior have been found using questions on lotteries, one of the most famous being the Allais paradox (Allais, 1953). A good description of the evidence can be found in Kahneman, Slovic and Tversky (1982), while more recent surveys are found in Machina (1987) and Camerer (1989). With this evidence in mind various theories have been developed to explain the observed deviations from expected utility theory. Typical examples of these theories are given by Bell (1982, 1985), Gul (1995), Kahneman and Tversky (1979), Loomes and Sugden (1982), Machina (1982), Quiggin (1982), Tversky and Kahneman (1992) and Viscusi (1989).

We choose to model the individual's decision process by Cumulative Prospect Theory (Tversky and Kahneman (1992)), which is the modern version of Prospect Theory (Kahneman and Tversky (1979)). We prefer Cumulative Prospect Theory (CPT) over the other theories, mainly because CPT remains closest to Expected Utility Theory in the sense that the value of a certain lottery does not depend on the other lottery that is offered. Another advantage is that more general problems (for example, choices out of sets of 3 lotteries) can still be handled with CPT, while the generalizations of the other theories are not clear. Machina's (1982) theory seems rather difficult to use in an empirical application and Gul's (1995) Disappointment Aversion is, given our data, observationally equivalent with Prospect Theory for a specific functional form of the probability transformations.[5]

CPT provides us with a representation of preferences, defined over lotteries on a real interval. Our discussion will concentrate on prospects, which are lotteries with a finite number of possible outcomes. General prospects are denoted by P and represent a set of n ordered outcomes $x_1 \leq \ldots \leq x_k \leq 0 \leq x_{k+1} \leq \ldots \leq x_n$, with corresponding probabilities $p_1, \ldots, p_n$.

In CPT the decision process consists of two phases: the editing phase and the evaluation phase. When deciding on the choice between lotteries an individual starts with the editing phase. The major operations in this phase are coding,

[5]Gul makes this observation when he discusses choices between binary lotteries on p. 677.

combination, and cancellation. In this phase the decision problem is also simplified. Dominated lotteries are rejected, very small probability events deleted and probabilities and outcomes rounded off. This phase already explains some of the expected utility anomalies reported in the literature. Even though we have very simple lotteries, this phase might be relevant, since there might be shifts in reference points or other types of framing effects. Evidence on the presence of framing effects is documented in, for example, Hershey and Schoemaker (1985) for the difference between probability equivalence questions and certainty equivalence questions. Recently, Seidl and Traub (1997) discuss the differences and possible causes for a broader range of questions. A more general discussion about framing effects can be found in, for example, Kahneman, Slovic, and Tversky (1982) and Tversky and Kahneman (1991).

In the evaluation phase CPT preferences over (edited) prospects are represented by a sign and rank-dependent functional, $V(P)$, which is defined as follows:

$$\begin{aligned} V(P) &= \Sigma_{j=1}^{k} \left(w^{-}(\Sigma_{i=1}^{j} p_i) - w^{-}(\Sigma_{i=1}^{j-1} p_i)\right) v(x_j) \\ &+ \Sigma_{j=k+1}^{n} \left(w^{+}(\Sigma_{i=j}^{n} p_i) - w^{+}(\Sigma_{i=j+1}^{n} p_i)\right) v(x_j) \end{aligned} \tag{4.1}$$

Here $v(x)$ represents a *value function* for money outcomes, which is strictly increasing and continuous. $v(0)$ is set to 0 as a normalization. $w^{+}(.) : [0,1] \rightarrow [0,1]$ and $w^{-}(.) : [0,1] \rightarrow [0,1]$ are *probability weighting functions,* which transform the cumulative distribution function to a new function, similar to a distribution function. $w^{+}(.)$ is used for outcomes in the positive domain, while $w^{-}(.)$ is used for negative outcomes. Both $w^{+}(.)$ and $w^{-}(.)$ are strictly increasing and $w^{+}(0) = w^{-}(0) = 0$ and $w^{+}(1) = w^{-}(1) = 1$.

The weights assigned to the values of the outcomes when evaluating a lottery are called decision weights. The decision weights result from the transformed cumulative distribution function in the same way as probabilities result from the cumulative distribution function. For example, for a positive outcome j the decision weight equals $\left(w^{+}(\Sigma_{i=j}^{n} p_i) - w^{+}(\Sigma_{i=j+1}^{n} p_i)\right)$.

One of the important features of CPT is that $v(.)$ is defined over the lottery prizes, which are changes in wealth and not final wealth. The model uses a reference point and thus allows the magnitude of the effect of a gain to be different from the effect of an equally large loss. Individuals now are supposed to choose the lottery with the highest V value.

There has already been extensive research (see, among others, Gonzalez and Wu (1999), Tversky and Kahneman (1992), and Tversky and Fox (1995)) on the properties of the decision weights as transformed probabilities and, in general, it is found that small probabilities are overweighted while larger probabilities are underweighted. An example of a probability weighting function, $w^+(p)$ or $w^-(p)$, is given in Figure 4.4.

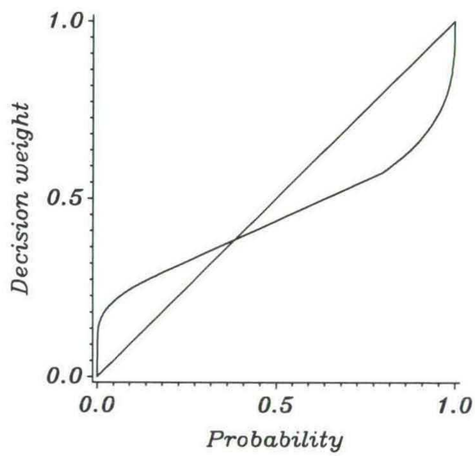

Figure 4.4: An example of a probability weighting function

Behavior towards risk is in CPT, unlike in expected utility theory, determined not only by the value function, $v(.)$, but also by the transformation of the probabilities, $w(.)$. There is some debate on what defines risk attitude within non-expected utility models, but for CPT a clear discussion of the two aspects is given by Wakker (1994). He separates the effects of risk aversion in terms of $v(.)$ and $w(.)$, where the effect of $v(.)$ is called decreasing, constant or increasing marginal utility, while the effect of $w(.)$ is called probabilistic risk aversion. The effect of $v(.)$ can be characterized by the usual Arrow-Pratt measure $-\frac{v''(x)}{v'(x)}$, while the effect of $w(.)$ is measured by its convexity which can be expressed similarly. Both a stronger decrease of marginal utility[6] and a more convex transformation from

[6]A stronger decrease of marginal utility for individual 2 compared to individual 1 is equiv-

probabilities to decision weights cause an individual to be more averse towards risk. The total effect depends on the prospect under consideration.

4.6 An empirical model for Cumulative Prospect Theory

The estimation results from the reduced form model in Section 4.4 show that individual characteristics influence an individual's choices in the questions that are asked, but it does not provide us with full information about the way this happens. Possibly an individual's value function varies with this index, but also the way probabilities are transformed into decision weights can be different across individuals. From the semiparametric estimation results we concluded that a single index may be too restrictive to model all the questions adequately. To test whether a model using different indices for the value and probability transformation function is able to fit all questions, one would like to use a structural model with separate indices for each of the questions. With such a model one can test whether the indices are the same for the different questions. Unfortunately, however, we cannot identify the decision weights, the value function and framing effects separately on the basis of one choice. For this reason we will not use the choice questions in the analysis that follows. For the probability equivalence questions the semiparametric estimation results showed that we can use the same index for the three questions. We use these three questions to determine the way in which the observed characteristics influence the decisions an individual makes. We use Cumulative Prospect Theory (CPT) to model the individual's decision process.

The most general specification of the CPT preference representation (4.1) for prospects with one positive outcome, x, with probability p and 0 otherwise is:

$$V_i(0,(1-p);x,p) \equiv w_i^+(p)v_i(x) \tag{4.2}$$

The subscript i indicates that the function depends on the individual. Since both w and v might vary across individuals we want to allow both functions to depend on an individual's observed characteristics. We thus allow each function

alent with $v_2 = \phi \circ v_1$, with ϕ a continuous, concave and strictly increasing function. We will call v_2 more concave than v_1.

to depend separately on an index, $x_i'\beta_v$ for v and $x_i'\beta_w$ for w, where x_i is a vector of observed characteristics and β_v and β_w are vectors of parameters that have to be estimated. Linearity of the index is not such a strong assumption since the index is allowed to enter the model nonlinearly. With this specification we do not need to normalize β_v and β_w. If β_v and β_w are the same up to a multiplicative factor, the model is a single index model as in Section 4.3.

For the choice of the functional form of the value function, v_i in (4.2), we follow the approach by Tversky and Kahneman (1992), and use the power function $v_i(x) = (x)^{\alpha_i}$, where we allow α_i to depend on the index $x_i'\beta_v$ quadratically,[7] so $\alpha_i = \alpha^0 + x_i'\beta_v + \alpha^1(x_i'\beta_v)^2$.

For the probability weighting function, w_i^+ in (4.2), we take the specification that is implied by the axiomatization of Prelec (1998), Proposition 1(A), so $w_i^+(p) = \exp(-(-\ln p)^{\gamma_i})$, where we allow γ_i to depend on the index for the probability weighting function $x_i'\beta_w$ in an affine way, so $\gamma_i = \gamma^0 + x_i'\beta_w$. The more general form of $w^+(p)$ as presented by Prelec in proposition 1(B) is not identified given our choice for $v(x)$.

In general, the effect of γ_i in the probability weighting function on an individual's risk attitude is not straightforward, since it is not directly linked to the convexity of the probability weighting function. The effect of α_i in the value function, however, is clear. A lower value of α_i implies a more concave value function and thus more aversion towards risk. We define more risk aversion as having a more concave value function and thus a lower value of α_i.

For the probability equivalence questions we assume that the respondents answered the questions in such a way that they are indifferent between the amount of money for sure and a lottery with a prize of Dfl 20,000, which might be won with the probability they answer. This implies that, for example, PE^1 satisfies the following equality: $w^+(\frac{PE^1}{100})v(20,000) = v(200)$. However, given the empirical evidence on framing effects, we want to allow for such effects. We cannot distinguish between the framing effects of the type of question we use, compared to other types of questions such as certainty equivalence questions, but we can identify differences between the questions. The framing effects we will estimate are based on the differences between the questions that are not explained by

[7] The indices are calculated using centered explanatory variables so the average for the indices is 0.

the CPT model. The estimates of the CPT parameters, especially the level of risk aversion, are still influenced by the fact that we use probability equivalence questions instead of an other type of question.

The estimated framing effects might contain systematic differences due to misspecification of our model, but in general framing effects are the result of a different interpretation by the respondents due to different questions. With our questions the respondents might adjust their reference point, since there is the possibility of having an amount of money for sure. If this is the case, this causes systematic differences between the model's predictions and actual behavior. The extent to which the reference point is adjusted might even depend on the amount of money. Such behavior is difficult to model explicitly and we allow for such factors by allowing the level of α_i to vary over the questions. We assume that the framing effects, denoted by f^1, f^2, and f^3 for PE^1, PE^2, and PE^3 respectively, are additive constants to α_i in each question. For PE^1, α_i increases with f^1 and similarly f^2 and f^3 are added to α_i for PE^2 and PE^3, respectively. Since the framing effects are not identified separately from α^0, we assume that the average framing effect equals zero. We thus set $f^1 + f^2 + f^3 = 0$ as an identifying restriction. We will distinguish between v_i, which is the individual's value function, and v_i^f, which is the individual's value function taking framing effects into account. v_i is the same for each question, while v_i^f can vary across the questions due to the framing effects. Notice that we assume that the probability weighting function is the same for each question and not affected by framing effects. This is only by assumption; the same results, but with a different interpretation, can be obtained if we fix the value function and allow the probability weighting function to vary across the questions in a specific manner. This should be taken into account when interpreting the results. The estimation results for the indices that control the variation between individuals are not influenced by the assumption that only the value function is influenced by the framing effects.

To allow for measurement error and unobserved heterogeneity we introduce a random component with a lognormal distribution in our model. For PE^1 our final model including both the random component and the framing effects will be:

$$w^+(\frac{PE^1}{100})v^f(20,000)\eta_1 = v^f(200), \tag{4.3}$$

with $\eta_1|x \sim \text{Lognormal}(0,\sigma_1^2) = LN(0,\sigma_1^2)$

$$w^+(p) = \exp\{-(-\ln(p))^{\gamma_0+x'\beta_w}\}$$

$$v^f(x) = x^{\alpha^0+x'\beta_v+\alpha^1(x'\beta_v)^2+f^1}$$

The same specification is used for the other two questions with the framing effect and the value 200 replaced by the corresponding values for the other questions. To take into account the fact that we observe three questions for each individual and to allow for unobserved heterogeneity and measurement error in the answers to the questions we specify a general correlation structure between the errors for the different questions. The distribution of $\eta = (\eta_1, \eta_2, \eta_3)'$ is $LN(0, \Sigma)$, with Σ a full covariance matrix and η is assumed to be independent from x.

Table 4.8: Estimation results for β_v and β_w. Standard errors in parentheses.

100*	β_v	β_w
Female	-2.077 (0.375)	-1.073 (0.592)
Age	-0.094 (0.015)	0.094 (0.022)
Log(inc)	0.613 (0.194)	1.001 (0.278)
Edu	0.891 (0.104)	-0.100 (0.136)
Dinczero	4.452 (2.014)	9.252 (2.771)
Dhp	2.600 (0.817)	1.253 (1.401)
Dgovemp	-0.757 (0.532)	-0.058 (0.759)
Dprivemp	-0.213 (0.473)	2.010 (0.649)
Dselfemp	0.135 (0.639)	0.920 (1.025)
Dmarried	-0.511 (0.412)	-3.139 (0.952)
Log(Wealth)	0.185 (0.041)	0.160 (0.057)

We estimate the model using maximum likelihood. Table 4.8 presents the estimates for β_v and β_w using a larger set of explanatory variables than the one we used with the semiparametric estimation technique.[8] The estimate for β_v shows that, for example, an individual that is ten year younger, *ceteris paribus*, will have a value of α that is 0.009 higher, on average. The same holds for a person with an income that is about 18% higher. Larger differences can be found

[8] Using this large set of explanatory variables with the semiparametric estimation method is not feasible.

between males and females, where the average value of α for females is 0.02 lower than for males, indicating that females are more risk averse than males. A similar difference is found between heads of household and their partners, if we compare them with the other respondents in the panel. From the employment dummies we can conclude that public servants are more risk averse than selfemployed. This difference, however, is only small and insignificant. The effect of wealth is as one would expect: the level of risk aversion decreases with wealth. Notice that the effects of wealth, income and education level all have the same sign and thus strengthen each other.

For the index controlling the variation of the probability transformation with observed characteristics we find significant effects of age, income, wealth, and the dummies for being married and employed in the private sector. Income, wealth, and being employed in the private sector have a positive effect on the index and thus correspond to less transformed probabilities.

The fact that the probability weighting function and the value function depend on the individual's characteristics through different indices conflicts with the semiparametric model, which is based on the assumption that there is only one index influencing the individual's decision process. It is interesting to know to what extent the two indices are able to explain the variation across respondents. If we take as a measure of fit the variance of the point forecasts[9] relative to the variance of the answers, this measure is less than 0.004 for each question if we set $x_i'\beta_v = 0$, so the explained variation due to the variation in the probability weighting function is small. If we set $x_i'\beta_w = 0$, this measure is 0.02, 0.08, and 0.14 for PE^3, PE^2, and PE^1, respectively, so the variation due to $x_i'\beta_v$ is much more relevant for the variation in the answers than the variation due to $x_i'\beta_w$. Still the restriction on the model that the probability weighting function is the same for each individual is strongly rejected.

For comparison we also estimated the model with the same set of explanatory variables as we used in the estimation of the semiparametric model. The estimate for β_v from the parametric model is very similar to the estimate from the semiparametric model and we do not report the results here separately. The results from the semiparametric model are thus very closely related to the variation in v, giving us a possible interpretation for the semiparametrically estimated index

[9]The point forecast for PE^1, for example, is $w^{+-1}(\frac{\hat{v}(200)}{\hat{v}(20{,}000)})$.

$x_i'\beta^{PE}$. This confirms the fact that the variation in answers due to variation in the decision weighting function is only small.

Table 4.9: Estimation results for the CPT parameters. Standard errors in parentheses.

Parameters for w	Parameters for v	
γ^0	α^0	α^1
0.394 (0.006)	0.353 (0.004)	8.555 (1.602)

The parameters determining the shape of the probability weighting function and the value function using the large set of explanatory variables are presented in Table 4.9. For the decision weighting function we see that the estimate for γ^0, the parameter that determines the level of γ, is 0.394 and significantly different from 1, which is the value of γ when the decision weights are equal to the probabilities and expected utility is valid. The value of γ_i for each respondent is determined by adding the index $x_i'\beta_w$ to γ^0. The values of γ_i in our sample range from 0.30 to 0.47. Given the estimated value function expected utility is strongly rejected.

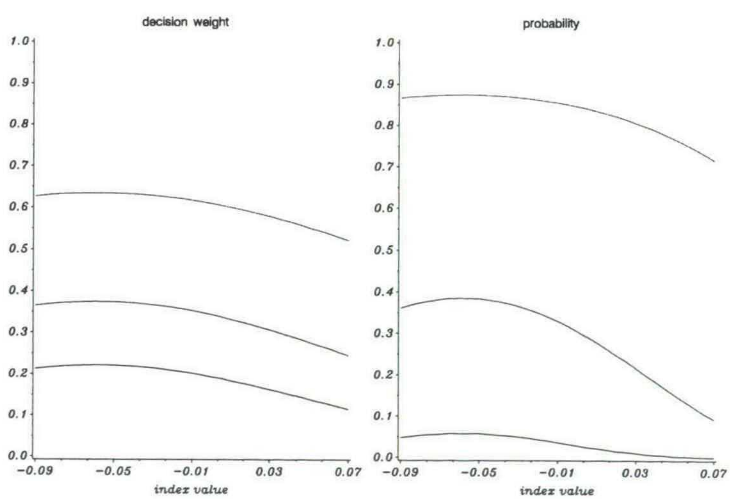

Figure 4.5: Predictions from the estimated CPT model excluding framing effects.

The estimates for α imply that, with the index $x_i'\beta_v$ varying between -0.089 and 0.069, the values for α_i are between 0.32 and 0.46 so for each individual

$\alpha_i < 1$, which indicates that individuals have decreasing marginal utility. The estimates for β_v and α^1 show that there is significant variation in the level of α_i. The size of the variation is, however, difficult to derive from these numbers. To give an idea about the variation across individuals and the predictions from our model, we plotted v_i, the part of v_i^f that is independent of the framing effects, for the three questions (with corresponding amounts of money) for different values of the index, $x_i'\beta_v$. This is plotted in the left panel of Figure 4.5. Note that higher values of $x_i'\beta_v$ correspond to lower levels of risk aversion. We normalized the scale of v_i such that $v_i(20,000) = 1$. With this normalization v_i, evaluated at the amount of money that is relevant for the question, equals the decision weight that is needed to be indifferent between the lottery ticket and the amount of money for sure as follows from (4.3). The variation in the predicted values for the decision weights in this figure is the effect of differences across individuals in the value function.

What we actually observe in the data are not the decision weights, but probabilities. In the right hand panel we plotted the probabilities that correspond to the decision weights in the left hand panel.[10] Due to the transformation of the probabilities to decision weights there is more variation in the answers than would have been the case if respondents did not transform the probabilities.

Table 4.10: Estimation results for the framing effects. Standard errors in parentheses.

f^1	f^2	f^3
-0.125 (0.002)	-0.048 (0.001)	0.174 (0.003)

The estimates for the framing effects of the differences between the questions are presented in Table 4.10. The framing effects are highly significant and imply higher answers for PE^1 and PE^2, while for PE^3 the answers are lower than without the framing effects. One of the reasons for this could be that our choice of functional forms is wrong, but a shift in reference points induced by the different amounts in the questions seems a better explanation. Making the reference point endogenous in the model, however, is rather difficult.

Figure 4.6 presents the same model predictions as Figure 4.5, but now v_i^f

[10] Since the probability weighting function differed across individuals through a second index, $x_i'\beta_w$, we set this index to 0 and used the 'average' probability weighting function with $\gamma = 0.394$.

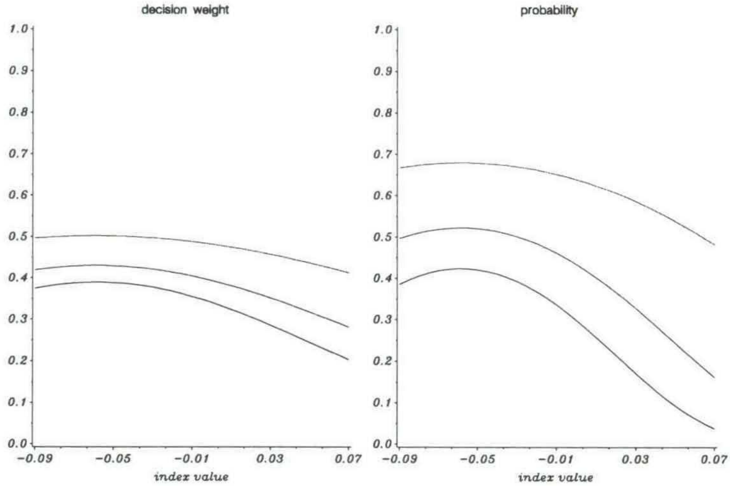

Figure 4.6: Predictions from the estimated CPT model including framing effects.

is used instead of v_i. The value function that is used to evaluate the different lotteries thus depends on the question. Comparing Figure 4.5 with Figure 4.6 we see that there is a clear need to understand framing effects in more detail, since they have a large impact on model predictions. We can conclude from these figures, however, that there is substantial variation in attitude towards risk across individuals and that we are able to predict part of this variation.

Table 4.11: Estimation results for the parameters in Σ.

Parameter	Estimate	Parameter	Estimate
ρ_{12}	0.831 (0.006)	σ_1	0.370 (0.009)
ρ_{23}	0.794 (0.007)	σ_2	0.363 (0.008)
ρ_{13}	0.593 (0.014)	σ_3	0.365 (0.007)

The estimates for the parameters in Σ are presented in Table 4.11. The correlation between the errors for the different questions for each individual are high, as could be expected. This indicates that there is still a lot of systematic variation at the individual level after we have taken out the systematic variation due to the observed characteristics.

4.7 Conclusion

In this paper we use data from the Dutch CentER Savings Survey. In this survey a set of hypothetical questions on lotteries is present. The respondents did not have monetary incentives when answering the questions so we started with validating the data by comparing the answers to the questions on lotteries with actual behavior and a second self-reported measure of risk attitude. It turns out that there are very strong and significant relations between the answers to the lottery questions and the other measures of risk aversion. Our data thus support the view that for simple choice problems real incentives are not necessary to elicit preferences.

Using the answers to a set of eight question on lotteries, we investigated whether attitudes towards risk are related to some commonly observed individual characteristics. Using semiparametric estimation techniques we find significant relationships between the answers to the questions on lotteries and age, gender, income, and education level. Females and older people have a more negative attitude towards risk, while income and education level are positively related to an individual's attitude towards risk. We focussed on the index that is derived from three probability questions and, even though we rejected the hypothesis that we could use a single index for all the questions, we found positive relationships between the choices that are made in the choice questions and the index derived from the probability equivalence questions. It thus seems justified to use such an index as a general measure of risk aversion. Implementing this measure of risk aversion into a model for savings or asset holdings could be used to prove the usefulness of measuring individual risk aversion, but this is left for future research.

To obtain more insight into the way the decision processes differ across individuals, we estimated a parametric model based on CPT. The specification allowed the value function and the probability weighting function to depend on the observed characteristics through two separate indices. Also systematic deviations from the model, due to, for example, framing effects, are allowed for.

The probability weighting function varies systematically with age, income, and wealth, while the value function depends on age, gender, income, education level, and wealth. It turns out that if we restrict our attention to the variables used in the semiparametric model, the estimated index for the value function closely resembles the semiparametric estimate. This gives a nice interpretation to the results from the semiparametric model: The semiparametrically estimated index seems to be related to the value function.

Using the decomposition of attitudes towards risk into decreasing/increasing marginal utility and probabilistic risk aversion our results indicate that individuals have decreasing marginal utility. Higher values for the estimated index imply a stronger decrease of marginal utility. Our specification does not allow us to say anything about probabilistic risk aversion, but the decision weights are significantly different from the true probabilities. For older people and females the difference is largest, while income has a negative effect on the difference.

These results are, however, based on the current specification, whereas complete identification of the influence of the value function and the probability transformation can only be based on a richer set of questions. One possibility to do this might be the use of a very large questionnaire as was done by Kahneman and Tversky, but it seems more fruitful in a survey to incorporate a shorter, but well designed set of questions. The ideas of Wakker and Deneffe (1996) on how to identify the utility function without specification of the decision weights might be a good starting point for this.

4.A Data

Questions

The first type of questions are the probability equivalence questions. In this type of questions, the probability is asked which would make the individual indifferent between a lottery ticket with probability p of winning 20,000 or a prespecified amount of money for sure.
The exact question is:

Imagine you have won Dfl amount$_k$ *in a game. You can now choose between keeping that Dfl amount*$_k$*, or having a lottery ticket with a certain chance to win a prize of Dfl 20,000.*

How high would that chance to win Dfl 20,000 have to be such that you would prefer the lottery ticket to keeping the Dfl amount$_k$ *that you had already won?*

I would prefer the lottery ticket if the chance to win the first prize would be at least.......... PE^k%

This question was asked three times, with amount$_k$ being Dfl 200, Dfl 1,000, and Dfl 5,000.

The second type of question is on choices between two opportunities, where preference for one or the other has to be stated.

The following information is given to the individuals.

You are probably familiar with games shown on television, where people win prizes and can choose between several options. For example, they can choose to keep a certain prize, or they can choose to take a chance to get a much bigger prize, at the risk of losing the prize all together.

The following questions present similar choices, concerning amounts of money. Some of the amounts are certain for you to have, others you can win in a lottery.

We would like to know which choice you would make. There are no right or wrong answers with these questions.

CH^1 We toss a coin once. You may choose one of the following two options:

- You receive Dfl 1,000 with either heads or tails
- With heads you receive Dfl 2,000, with tails you don't receive anything at all.

CH^2 Which of the following two options would you choose?

- You draw a lottery ticket with an 80% chance to win Dfl 45 (if you loose, you don't get anything at all)
- You win Dfl 30, no matter which ticket is drawn.

CH^3 Which of the following two options would you choose?

- You draw a lottery ticket with a 25% chance to win Dfl 100 (if you loose, you don't get anything at all)
- You draw a lottery ticket with a 20% chance to win Dfl 130 (if you loose, you don't get anything at all)

CH^4 Which of the following two options would you choose?

- You draw a lottery ticket with a 2% chance of winning Dfl 3000 (if you loose, you don't get anything at all)
- You draw a lottery ticket with a 1% chance of winning Dfl 6000 (if you loose, you don't get anything at all)

CH^5 We toss a coin once. Would you accept the following agreement? (yes/no)

- Heads, you win Dfl 1,500.
- Tails, you lose Dfl 1,000

Descriptive statistics

This appendix contains the definition and some descriptive statistics of the variables that are used as independent variables in the models that are estimated.

Table 4.12: Description of some variables

Variable	Description	Mean	Std. dev.
Age	Age (in years)	42.1	14.18
Female	Dummy; 1 if female	0.43	0.50
Education	Education level, 1,3,5	3.31	1.67
Log(Income)	Log(gross annual individual income)	8.70	4.27
Dinczero	Dummy; 1 if income equals zero	0.18	0.39
Dhp	Dummy; 1 if head or partner	0.91	0.29
Dgovemp	Dummy; 1 if employed in public sector	0.16	0.37
Dprivemp	Dummy; 1 if employed in private sector	0.44	0.50
Dselfemp	Dummy; 1 if self employed	0.08	0.27
Dmarried	Dummy; 1 if married	0.80	0.40
Log(Wealth)	Log(financial wealth)	7.39	4.45

4.B Semiparametric estimation method

In this appendix we describe the method of estimation we use for the semiparametric model of section 4.3. We give a short description of the assumptions we make and the choices for the bandwidths in the semiparametric estimators.

The main assumption is that for each question the distribution of the answers for an individual i with characteristics x_i depends on x_i only though an index $x_i'\beta$. Let y_i be individual i's answer to the question under consideration. We then have that $f(y_i|x_i) = f(y_i|x_i'\beta)$, where $f(y_i|x_i)$ denotes the density function of y_i given x_i. Let $E\{y_i|x_i'\beta\}$ denote the expectation of y_i given $x_i'\beta$, then we can write the monotonicity assumption we make as $E\{y_i|x_i'\beta\} = G(x_i'\beta)$, with $G'(.) > 0$. We also use a normalization for the parameter relating to gender. Preliminary analysis showed that this variable had a significant influence on the answers, making it a valid parameter for the normalization. For the estimator to be consistent, there also needs to be at least one continuous variable that has a nonzero coefficient. Both age and income can satisfy this condition, but, due to the high correlation between these two variables, it can be the case that only one of these variables is significant and it is not clear a priori which one is.

With these assumptions and some regularity conditions we can use the rank estimator proposed by Cavanagh and Sherman (1998) (CS) to obtain a $\sqrt{N}$−consistent estimate for β in each question. The estimator of CS is defined as:

$$\hat{\beta}^{rc} = \arg\max_{\beta} \frac{1}{N} \Sigma_{i=1}^{N} y_i R_N(x_i'\beta), \tag{B.1}$$

with $R_N(x_i'\beta) \equiv \Sigma_{j=1}^{N} I\{x_i'\beta \geq x_j'\beta\}$, the rank if $x_i'\beta$. CS prove that the objective function is asymptotically smooth, even though the rank of $x_i'\beta$ is not a smooth function. The small sample properties of the estimator, however, are not so nice and optimization of the objective function turns out to be problematic in our case. To overcome the small sample problems of the estimator we smooth $R_N(x_i'\beta)$ as follows:

$$R_N^s(x_i'\beta) = \Sigma_{j=1}^{N} F(\frac{x_i'\beta - x_j'\beta}{h_N}), \tag{B.2}$$

with $F(.)$ the cumulative distribution function for the logistic distribution and h_N a smoothness parameter satisfying $h_N \to 0$ as $N \to \infty$.

The initial $\sqrt{N}$−consistent estimate is now defined as:

$$\hat{\beta}^{rcs} = \arg\max_{\beta} \frac{1}{N}\Sigma_{i=1}^{N} y_i R_N^s(x_i'\beta). \tag{B.3}$$

Optimization of the objective function is performed with a Simplex algorithm. This works well in practice. The estimate is not sensitive to the choice of h_N in the smoothed rank. For practical purposes we set $h_N = 0.1\sigma$, with σ the estimated standard deviation of $x_i'\beta$, although it might not be valid to let h_N depend on the estimated parameter.

With this initial estimate a semiparametrically efficient estimate is constructed using a one-step improvement as proposed by Delecroix, Härdle, and Hristache (1997). We define $L_n(\beta)$ as $\frac{1}{N}\Sigma_{i=1}^{N}\log(f(y_i|x_i'\beta))$, the likelihood function. Since we do not know $f(y_i|x_i'\beta)$ we have to estimate it. This is done using kernel estimates. We define $\hat{L}_n(\beta)$ as $\frac{1}{N}\Sigma_{i=1}^{N}\log(\hat{f}(y_i|x_i'\beta))$, with

$$\hat{f}(y|x'\beta) = \frac{\frac{1}{N}\Sigma_{i=1}^{N}\frac{1}{hy}K(\frac{y-y_i}{hy})\frac{1}{hx}K(\frac{(x-x_i)'\beta}{hx})}{\frac{1}{N}\Sigma_{i=1}^{N}\frac{1}{hx}K(\frac{(x-x_i)'\beta}{hx})} \tag{B.4}$$

The efficient estimate is now defined by

$$\hat{\beta} = \hat{\beta}^{rcs} - (\frac{\partial^2 \hat{L}_n}{\partial\beta\partial\beta'}\left(\hat{\beta}^{rcs}\right))^{-1}\frac{\partial \hat{L}_n}{\partial\beta}\left(\hat{\beta}^{rcs}\right), \tag{B.5}$$

as long as $\frac{\partial^2 \hat{L}_n}{\partial\beta\partial\beta'}\left(\hat{\beta}^{rc}\right)$ is negative definite. The gradient and Hessian need to be computed using fourth order kernels. In small samples this can be problematic since the density estimates can be negative. Instead of using the theoretically required fourth order kernels, we will use a variable bandwidth kernel density estimator (see Hall (1990) and Hall and Marron (1988)), which yields the same bias reduction, while at the same time the density estimate is guaranteed to be positive. Numerical derivatives are used to compute the gradient, while the Hessian is computed as the outer product of the gradient.

For the variable bandwidths we set $h_x = 0.0625\hat{f}(x'\hat{\beta}^{rcs})$ in de denominator, $h_x = 0.0625\hat{f}(y, x'\hat{\beta}^{rcs})$ in the numerator and $h_y = 0.125\hat{f}(y, x'\hat{\beta}^{rcs})$, where $\hat{f}(y, x'\hat{\beta}^{rcs})$ and $\hat{f}(x'\hat{\beta}^{rcs})$ are kernel estimates for the joint distribution of y_i and $x_i'\hat{\beta}^{rcs}$, and the marginal distribution of $x_i'\hat{\beta}^{rcs}$, respectively. Although Delecroix, Härdle and Hristache (1997) provide no theoretical justification for a data dependent bandwidth, as we use for the variable bandwidth kernel density estimator, we choose this approach on practical grounds. The advantages of a guaranteed positive density and a bias reduction that is the same as for fourth order kernels are large.

The values for the bandwidths are based on visual observation. Since the method described above uses undersmoothed bandwidths, we select bandwidths in the region where the density estimates are not very smooth. Within a large range of bandwidth choices the estimates did not vary very much. Standard errors for the estimates are also computed using numerical derivatives. They were more sensitive to the choice of bandwidths, but, for a reasonable range of bandwidths, they do not differ by more than 25% from the estimates we present here.

Chapter 5

Explaining time preference anomalies: a quantification

Elicitation of individual rates of time preference is a difficult task. Different questions for eliciting time preference, in general, result in large intrapersonal differences in the observed discount rates. This behavior is very difficult to rationalize with the traditional discounted utility model. However, there is a claim in the economic psychology literature that reference point dependent preferences are able to explain this behavior, but in empirical applications such a model has never been explicitly used. In this chapter we estimate a structural model for the individual's decision making process that is based on a reference dependent value function. We allow the model parameters to vary with observed individual characteristics. Our main finding is that although implied discount rates vary substantially between different scenarios, this behavior can be explained using a simple model with scenario independent parameters. We find low discount rates and a significant effect of loss aversion in the preference specification. The variation in the level of loss aversion is small, but significant, and discount rates vary significantly with age, gender, and income.

5.1 Introduction

Most, if not all, economic decisions have consequences at different points in time. In order to make decisions with such a time dimension rationally, one has to compare benefits and costs occurring at different points in time. Samuelson's

(1937) discounted utility model is the single most important tool for analyzing such intertemporal choices. The main feature of this model is that the present subjective value of a future reward or pleasure decreases with the distance in time of the event. Temporal discounting or time discounting reflects the assumption that individuals are impatient. People prefer to consume things now rather than tomorrow.

Since many economic decisions involve a time dimension, the rate of time preference, i.e., the speed at which the current subjective value of an outcome in the future decreases with the length of the delay, plays a crucial role in economics. Information about discount rates is highly relevant, for example, for economic growth, since the rate of time preference is strongly correlated with savings and the growth rate of consumption (see Epstein (1983) and Ogaki and Atkeson (1997)).

The rate of time preference also has a large impact on all types of investment decisions. An example of an investment decision that is important in economics is the decision on how much schooling to obtain. Impatient individuals are more likely to quit school and start earning money in the labor market. Lang and Ruud (1986) studied the impact of time preference heterogeneity and did not find strong relationships between the discount rate that is implicit in the education decision and a small set of observed characteristics. Belzil and Hansen (1999), however, use an unobserved heterogeneity term for the subjective discount rate and show that the rate of time preference plays an important role in estimating the return to schooling. They show that if one estimates the return to schooling without controlling for heterogeneity with respect to individual discount rates, the estimated returns to schooling have a substantial upward bias. Direct information on individual discount rates, like the estimates we obtain in this chapter, could be very helpful in studies where one should correct for heterogeneity with respect to the rate of time preference. Examples are not only studies on the education decision and the returns to schooling, but also studies on home ownership decisions or the purchases of durables. As a last example governments can use information on which individuals discount heavily to focus long-term savings plans on these groups in the population. In the special case of retirement savings Samwick (1998) discusses the importance of time preference heterogeneity for social security reforms. In general, one can state that every economic model that deals with consumption, saving, or investments should take the rate of time preference into account and also its variation across individuals.

One of the first papers that actually tried to estimate the rate of time preference is Hausman (1979). He derived the rate of time preference from the decision to buy a more expensive but also more energy-efficient air conditioner instead of a cheaper, less energy-efficient version. The trade-off that is made in this decision, is between the purchase price now and the cost of electricity used in the future. The estimated individual annual discount rates[1] ranged from 14% to 25%. These estimates are fairly high compared to market interest rates, favoring the inefficient types more than if the decision is based on the market interest rate. Thaler (1981) estimated discount rates using questions that are more directly related to time discounting. He also found large individual discount rates and, in addition, large changes in the observed discount rates when the questions were framed differently. Annual discount rates differed systematically with the amount of money used in the question, whether it was a gain or a loss, and with the time period. Similar results were obtained by Loewenstein (1988), Benzion, Rapoport, and Yagil (1989), and Shelley (1993). Green et al. (1997) focussed on discount rates for different amounts of money and different delay lengths and found significant differences.

These findings cannot be reconciled with the traditional model of time discounting as developed by Samuelson (1937), and the axiomatic derivation of this model by Koopmans (1960), since they assume that the discount rate is independent of the quantity that is discounted. With these observed anomalies in mind, a number of theories have been proposed that provide explanations. Recently, Loewenstein and Prelec (1992) and Shelley (1993) devised a framework capable of explaining most anomalies. The preference specifications they propose use a reference point dependent value function. Preferences with such a value function do not integrate the outcomes proposed in the questions with the situation as it was before, but evaluate the proposed changes from a certain reference point. The main feature of such preferences is that they treat gains and losses asymmetrically. With this type of preferences losses are usually more influential than gains. For an extensive discussion of loss aversion and reference dependent choice models in different contexts, see Tversky and Kahneman (1991).

[1] If r is the discount rate, then the corresponding discount factor equals $\frac{1}{1+r}$.

The main focus of the literature on time preference has been on the systematic differences in the answers to questions that differed on aspects that are not expected to influence the discount rates. These different settings of the questions are called scenarios. They usually differ with respect to the amount of money that is considered, whether this is a payment or a receipt, or, of course, the length of the time interval between the two payments or receipts. The systematic differences in the observed discount rates between scenarios are then used to show the relevance of the proposed models. In general, the data are summarized by reporting means for different questions and then interpreting the differences between these cell means. To the best of our knowledge, however, no one has followed a structural approach to estimate a discounted utility model that allowed for reference dependence and loss aversion. In this chapter we estimate a structural model of the individual's decision making process that incorporates reference dependence and loss aversion. Systematic variation of the parameters in the structural model across individuals is allowed for. Estimation of a structural model is needed to better understand individual behavior and to predict behavior in new situations.

Our model is based on the intertemporal choice model proposed by Loewenstein and Prelec (1992). We quantify the different aspects of their model. The most important aspect of their model which makes it different from the traditional discounted utility model is the presence of loss aversion. The model is estimated using data from a large Dutch household survey, the CentER Savings Survey, which contains several questions on time discounting. One of the most interesting topics is whether the empirical model is capable of explaining the observed differences between the implied discount rates from the different questions with parameters that do not depend on the questions themselves.

In addition to the differences between the various scenarios, we are also interested in differences between individuals. We will relate some of the parameters in the model to observed characteristics such as gender, the presence of children in the individual's household, income, and age.

The remainder of this chapter is structured as follows: Section 5.2 describes the data. The model proposed by Loewenstein and Prelec (1992) will be discussed in Section 5.3. Here special attention will be given to the interpretation of the questions. The empirical specification of the model is presented in Section 5.4. Section 5.5 presents the estimation results and Section 5.6 concludes.

5.2 Data

The data come from a large Dutch household survey, the CentER Savings Survey (CSS). We used the 1997 wave of the panel since this was the first year in which an improved set of 'time preference' questions was incorporated. In Chapter 2 we analyzed the time preference questions in two earlier waves and investigated the usefulness of such information in the prediction of economic decision making. All participating households have been provided with a personal computer and answer the survey questions directly on their PC; no personal interviews are held. The CSS is a rich source of data, including information on household composition, income, assets and psychological concepts. A detailed description of the survey and the data collection method can be found in Nyhus (1996).

In the part of the questionnaire concerning psychological concepts, a large number of questions have been asked to derive properties of individuals' utility or value functions. For example, there are questions that can be used to derive information about individuals' attitudes towards risk or individuals' rates of time preference. The latter questions can be divided into two groups. The first group consists of introspective questions concerning attitudes towards the future, such as: '*I react only to sudden problems*' and '*I will tackle the problems in the future when they are there*'. The second group of questions has a more quantitative nature and is based on experiments that have been carried out in the experimental psychology and economics literature, see Benzion, Rapoport, and Yagil (1989), Shelley (1993), and Green et al. (1997). The questions differ with respect to four characteristics. The first characteristic is the amount of money under consideration (either Dfl 1,000 or Dfl 100,000).[2] We refer to these two amounts as the low and high amount, respectively. The second characteristic is whether the amount of money has to be paid or is to be received. The third characteristic that is varied across the questions is whether the payment or receipt of the amount of money is planned immediately or in the future. The final difference between the questions is the time horizon for the question, which is either three or twelve months. Using a full factorial design of these four characteristics, each of them with two levels, we obtain a set of 16 quantitative questions.

Let's illustrate this with the question for the 3 months delayed receipt of

[2] Dfl 1 $\approx$ US\$ 0.5.

Dfl 1,000, which is as follows:

Imagine you won a prize of Dfl 1000 in the Staatsloterij (the State Lottery). The prize is to be paid today. Imagine further that the lottery asks you to agree with payment of the money in three months time. There is no risk that the money will not be paid.

What amount of money would you demand AT LEAST as a compensation for the delay in payment with three months? If you would agree with the delay without a compensation, you can fill out 0.

At least a compensation of Dfl. ……

The *Staatsloterij* is a national lottery organized by the state. The statement that there is no risk that the money will not be paid represents the general opinion about it and matches reality.

The same question is then asked with a delay of one year. Both questions are then asked with a prize of Dfl 100,000. For the questions on losses (payments instead of receipts) an assessment of tax arrears is used instead of a prize in a lottery. The precise questions for the delay payment scenario, the speed up receipt scenario, and the speed up payment scenario are presented in Appendix 5.A. Each of these scenarios is used four times; varying with respect to the two amounts of money and the two time delays. To simplify notation we will use some shorthand notation. Scenarios concerning a delay are denoted with *del* and speed up scenarios with *spe*. Similarly, receipts and payments are denoted by *rec* and *pay*, while the high and low amount will be H and L, respectively, and *3* and *12* denote the time delay in months. The question presented above concerns a $\underline{3}$ month $\underline{\text{del}}$ay of a $\underline{\text{rec}}$eipt of the $\underline{\text{L}}$ow amount of money, so this scenario will be referred to as *delrecL3*.

When asking questions about attitudes, it is well known that respondents have a tendency to give answers that are socially acceptable or desirable. Asking for more money seems greedy, which is not a desirable characteristic, at least for most people. This might result in a bias towards zero in the answers to the questions, especially since the number zero is mentioned in the questions. The fact that respondents type in the answers on a computer, without the presence of an interviewer, however, is likely to reduce this bias, if it is present.[3]

The sample of respondents answering the psychological questionnaire, which contains the questions on time preference, consists of 2663 individuals. A total of 821 answers, given by 282 respondents, are so high that they imply a discount rate of at least 100%. We assume that these respondents did not fully understand the question and that they did not report the change in the amount of money, but possibly the resulting amount of money including the receipt or payment itself. After taking out the amount of money still 126 answers from 77 respondents imply discount rates of at least 100% for at least one question. These respondents are excluded from the analysis. The resulting sample consists of 2586 respondents.

Some descriptive statistics of the data are given in Tables 5.1 and 5.2. Table 5.1 presents the fraction of the respondents answering zero for a specific scenario and time/amount combination, while Table 5.2 presents the average implied discount rates, including the zeroes. The implied discount rate is defined as the discount rate, r, that satisfies the equality:

$$\text{amount of money now} = \frac{1}{1+r} \times \text{the amount of money in the future}$$

This is the measure of time preference that has been used in previous work on time preference. For the delay of three months the three months discount rates are reported. There are large differences between the answers to the questions for the various scenarios, amounts, and time delays. In the sequel we shall interpret these differences using an economic model. First, we present a model for intertemporal decision making in the next section.

5.3 A model for time preference

The traditional view on temporal discounting uses the concept of exponential discounting of outcomes at different moments in time with a constant rate of time preference. Although by now some people question the idea of exponential

[3]Using monetary incentives, as is frequently done in experiments on decision making under risk, is almost impossible with questions on time preference. Imagine a researcher asking a respondent to give him a certain amount of money. The researcher of course promises to pay this money back, including the desired interest rate. Such an experiment does not seem to make a lot of sense.

Table 5.1: Fraction of individuals answering zero

	delrec	*delpay*	*sperec*	*spepay*
H12	0.141	0.570	0.590	0.390
H3	0.194	0.614	0.676	0.391
L12	0.180	0.675	0.705	0.392
L3	0.336	0.766	0.817	0.418

Table 5.2: Average implied discount rates including zeroes

	delrec	*delpay*	*sperec*	*spepay*
H12	0.129	0.019	0.020	0.062
H3	0.050	0.008	0.007	0.027
L12	0.197	0.030	0.025	0.106
L3	0.075	0.016	0.008	0.049

discounting itself (see Laibson (1997), Loewenstein and Prelec(1992)), the first anomalies that were encountered by Thaler (1981) are of a different type. He found that the observed implied discount rates varied systematically with changes in the length of the time span involved, the amount of money involved, and whether it was a gain or a loss. Consequently, the model with a single discount rate for all outcomes was rejected. The findings of Thaler (1981) have been confirmed in many other studies, among others, Benzion, Rapoport, and Yagil (1989), Shelley (1993), and Green et al. (1996, 1997).

A model that tries to explain the differences between the observed discount rates in the various scenarios is presented by Loewenstein and Prelec (1992, LP in the sequel). We start with a short description of this model for decision making in the context of intertemporal choices. This description is followed by an interpretation of the data in the context of this model. The empirical implementation of this model is presented in the next section.

Let a sequence of dated outcomes be denoted by $\{(x_k, t_k);\ k = 1, \ldots, n\}$, meaning that outcome x_k occurs at time t_k for each k. LP start with a set of assumptions such that preferences over such sequences of dated outcomes can be represented by the usual additive and separable representation $U(x_1, t_1; \ldots; x_n, t_n) = \Sigma_k \phi(t_k) v(x_k)$. Here $\phi(t_k)$ is the discount factor for outcomes occurring at time t_k and $v(x_k)$ is the value given to an outcome x_k.

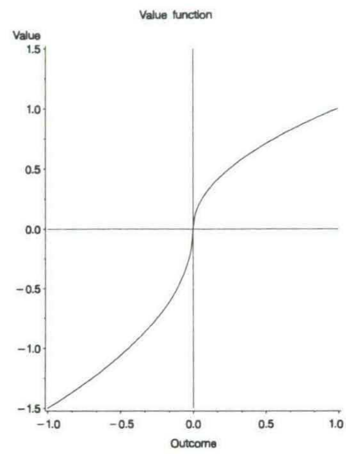

Figure 5.1: A reference dependent value function

The most important feature of the model is that it replaces the utility function in the traditional discounted utility models with a value function with a reference point. The value attributed to an outcome, x, given a certain reference point, r, is denoted by $v(x - r)$. Outcomes are thus evaluated as deviations from the reference point. Outcomes that are above the reference point are called gains and outcomes below the reference point are called losses. A crucial aspect of the model is that the reference point can depend on the individual's current situation. An example of this is the evaluation of a wage increase or decrease. Such a change in income is evaluated as either a gain or a loss. A simple reference point would be the current wage and depending on whether the wage increased or decreased one perceives a gain or a loss. The reference point, however, can also be determined by expectations. If a wage increase was expected and the actual size of the wage increase is lower than was expected, the increase in income will still be evaluated as a negative outcome, since it is lower than the reference point.

The properties of the value function, $v(x)$, are most easily explained using a picture, see Figure 5.1. The value function consists of two segments, one for gains and one for losses and a reference point, which has value zero due to normalization. Empirical evidence so far has suggested that the most important difference between the gain and loss segments of the value function is that the segment for losses is steeper than the one for gains, which is shown in the figure by the fact that $v(x) < -v(-x)$. Examples of studies on individual decision making where this phenomenon, called loss aversion, is observed are, among others, Prelec and Loewenstein (1991), Kahneman, Knetsch, and Thaler (1991), and Tversky and Kahneman (1991).

LP assume a flexible specification for the discount function, $\phi(t)$, which allows for hyperbolic discounting. Hyperbolic discounting is the phenomenon that the short term discount rates implied by observed behavior are significantly larger than the long term discount rates. This phenomenon and its consequences are discussed in detail in Laibson (1997). Loewenstein (1996) presents a better explanation of the phenomena that have resulted in the development of hyperbolic discounting. This theory of Loewenstein (1996) is based on self control problems resulting from visceral influences, like pain and hunger, and is very convincing. Rachlin (1996) in a comment on Loewenstein (1996) notes that: 'Loewenstein is therefore also correct to ignore overly-simplistic behavioral hyperbolic discounting models such as my own earlier model'.

The evidence of hyperbolic discounting that is based on hypothetical choice situations in the experiments on intertemporal choice is not so easy to explain using Loewenstein's theory. This evidence is also not very convincing, since a model with exponential discounting and a reference dependent value function generates the type of behavior that has been interpreted as evidence for hyperbolic discounting. A simple example can show this. Suppose we pose questions to an individual who discounts outcomes in time exponentially with an annual discount factor β. The value function of this individual is reference dependent with loss aversion. The value function is such that the value of a gain of size x equals x, while the value of a loss of size y equals $-\lambda y$, with $\lambda > 1$. The observed annual discount rates for this individual when a receipt is postponed for t years can be shown to be $\beta/\lambda^{1/t}$, if we assume that the individual has adjusted his reference point to obtaining the receipt now. The observed implied discount rate is thus decreasing over time even though the true discount rate, β, is constant.

Since we observe outcomes at only two different points in time, it is not difficult to allow for general types of discounting and we do not impose exponential discounting. The discount function is modelled with two discount factors, one for the delay of three months, ϕ^3, and one for the delay of one year, ϕ^{12}. If the delay length is either one of the two delay lengths, ϕ will denote the relevant discount factor. We can test for exponential discounting by testing whether $(\phi^3)^4 = \phi^{12}$.

The major problem when using reference point models in empirical implementations is the determination of the reference point. With the questions in our data it is not very clear what the reference point is when we model the behavior of the respondents. The respondents are asked to imagine that they have won a certain amount of money, but they are also immediately offered the opportunity to shift this amount of money over time. Respondents might or might not completely adjust to the imaginary situation of having won the amount of money. If respondents adjust to the hypothesized situation, the questions have to be interpreted as compensating variation questions, otherwise the questions are equivalent variation questions (see LP for this terminology).

For each of these two interpretations we can obtain equalities that the answers to the questions have to satisfy. Here we assume that the respondents answer such that they are precisely indifferent between shifting the amount of money in time and keeping the situation as it is initially proposed in the question. Let p denote the amount of money to be paid or received and y the respondent's answer, then, using the normalization $v(0) = 0$, we obtain the model equalities for the various scenarios and present them in Table 5.3. In the compensating variation interpretation the respondent has adjusted to the hypothesized situation, so the reference point is the situation with a payment or a receipt and the question refers to shifting this payment or receipt in time. For the equivalent variation interpretation the individuals did not adjust at all to the hypothesized situation and the reference point is the situation without any payment or receipt.

Table 5.3: Model equations for the questions.

Scenario	Compensating variation	Equivalent variation
delrec	$v(-p) + \phi v(p+y) = 0$	$v(p) = \phi v(p+y)$
delpay	$v(p) + \phi v(-(p+y)) = 0$	$v(-p) = \phi v(-(p+y))$
sperec	$v(p-y) + \phi v(-p) = 0$	$v(p-y) = \phi v(p)$
spepay	$v(-(p-y)) + \phi v(p) = 0$	$v(-(p-y)) = \phi v(-p)$

We take a closer look at the equality that has to be satisfied in the *delrec* scenario. In the compensating variation interpretation of this question the respondents completely adjust to having won the prize and they have to give up an amount of money today in order to get a possibly larger amount of money after a certain delay. Giving up the money today will be felt as a loss, $v(-p)$, which can have a larger disutility than the utility of receiving the money plus interest, $v(p+y)$. The amount of money in the future has to compensate the loss of the money today.

In the equivalent variation interpretation of this question the respondents compare a gain today, $v(p)$, with a possibly larger gain, $v(p+y)$, in the future. Here, the effect of loss aversion is far less clear cut. In the same way one can interpret the other equalities in Table 5.3.

There is one clear difference between the compensating variation and the equivalent variation interpretation. In the equivalent variation interpretation there are only comparisons of gains with gains and losses with losses. There is no role for loss aversion in this case. The differences between the various scenarios are only due to differences in curvature of the gain and loss segment and differences in curvature of the value function above and below the amounts of money mentioned in the questions. When we interpret the data, we will discuss what the shape of $v(.)$ would have to be, to be consistent with the observed behavior.

If we allow for loss aversion, meaning that $v(x) < -v(-x)$ for $x > 0$, and we take the compensating variation interpretation of the questions, the model equations imply that the *delrec* and *spepay* scenarios are very similar, since they both have a loss today and a gain in the future. The only difference between these two scenarios is due to the curvature of v. The same holds for the *delpay* and *sperec* scenarios, but with a gain today and a loss in the future. The differences between the delay receipt and speed up receipt scenario depend on the level of loss aversion. For the *delrec* and *spepay* scenario a loss today has to be compensated by a gain in the future. If loss aversion is present the gain has to be larger than in the case without loss aversion. Loss aversion thus implies higher observed discount rates for the *delrec* and *spepay* scenario compared to the *delpay* and *sperec* scenarios, where loss aversion has a negative effect on the observed discount rates. In the equivalent variation interpretation, where the respondents have not adjusted to the hypothesized situation, the model does not yield a clear indication of the differences between the observed discount rates. In the compensating variation interpretation, with adjusted reference points, however, the model yields clear predictions about the differences between certain scenarios. We will now discuss whether these predictions are in accordance with the data.

An interpretation of the data

We start with a discussion of the data assuming that the respondents adjust their reference point, which is the compensating variation interpretation. Table 5.1 shows that a large fraction of the respondents answers zero. An interesting question is whether this implies that these respondents have a zero or a negative rate of time preference. Given the presence of loss aversion it is not necessarily the case that the rate of time preference is non-positive for the *delpay* and the *sperec* scenarios, even though the answer is zero. In these scenarios the loss of money in the future results in such a negative utility that it is not compensated by the same gain now, even though the loss is discounted. Respondents are not willing to shift the amount of money in time as long as $\phi > \frac{v(p)}{-v(-p)}$. Loss aversion thus results in a *status quo* bias, see Kahneman, Knetsch, and Thaler (1991). Nyhus (1999) uses earlier waves of the CSS and interprets this unwillingness to change as indifference thresholds that vary across questions. These thresholds thus can be due to loss aversion. For the *delrec* and *spepay* scenarios loss aversion has a positive effect on the answers and is not an explanation for the zeroes in the data. Notice that the largest fraction of respondents that answer zero is found in the *delpay* and the *sperec* scenarios where the model can explain it. Another possible reason why respondents answer zero is that they find the compensation they need very small and they do not find it worthwhile to fill out this amount: the answer is not salient. The fact that a lower amount and a shorter time delay both increase the number of zeroes that are answered by the respondents supports this idea.

The average implied discount rates in Table 5.2 follow the same pattern as the number of zeroes, when we look at the differences between the scenarios. Looking at the differences in implied discount rates due to different time lengths and amounts, however, we see that the patterns for the averages and the number of zeroes are not the same. The number of zeroes increases systematically as the predictions from the model are lower. Lower amounts and a shorter time delay predict a lower implied discount rate and, indeed, the number of zeroes in the answers to these questions is larger than for the high amount and longer time delay questions. For the average discount rates, however, we see that the lower amount of money induces higher average discount rates, even including the larger number of zeroes. One explanation for this is that if the answer is positive, it will be substantial, since otherwise the reward is not salient, i.e., not significant.[4]

In the equivalent variation interpretation the model does not yield strong predictions for the possible differences between the different questions. Moreover, the model is not able to explain the zeroes at all, although this is a striking feature of the data. However, it is possible to model the data when we adapt the equivalent variation interpretation. Even though we have only information about ratios of marginal value, we can conclude that the value function we need in this situation is rather unusual. For the payment scenarios the data imply a value function for losses that does not satisfy the idea of diminishing marginal sensitivity, while the model can explain the receipt scenarios only with a value function that has a very strongly decreasing marginal value function for gains.

Using the compensating variation interpretation of the questions the model can give a good description of the main features of the data. The equivalent variation does not result in strong predictions for the outcomes and the type of value function needed to describe the data is not intuitively appealing. Nyhus (1999) also concludes that the data support the compensating variation interpretation, although she does not compare it directly with the equivalent variation interpretation. Her conclusion is based on a nonparametric test using pairwise differences between the implied discount rates of the various scenarios. Therefore the empirical model we use is based on the compensating variation interpretation of the questions.

5.4 Empirical model for time preference

The main focus in the literature on time preference has been on the differences between various scenarios, like the ones described above, with varying amounts of money and different time intervals. The observed differences were used to show the relevance of newly proposed models that generalize the discounted utility

[4] We could use unobserved thresholds for this in our empirical model. Given the large number of questions and the number of thresholds needed, this will complicate the model estimation substantially.

model. In general, the data were summarized by reporting means for different questions and then interpreting the differences between these cell means, similar to the interpretation of the data we gave in the previous section. In this chapter we estimate a model of the underlying decision process, where the parameters of the model are allowed to vary across individuals. This section presents the empirical model we use to estimate the individual's rate of time preference, based on the model presented in the previous section.

To estimate a structural model we have to choose specific functional forms for $\phi(t)$ and $v(x)$ and we also need to choose the way these functions vary across individuals. As already discussed in the previous section we want to allow for general forms of discounting. To do this we model the discount function of respondent i with two different discount factors, one for the delay of three months and one for the delay of one year.

Our focus is on the determination of the discount rates, taking into account the underlying decision process. The estimated discount rates can be sensitive to the specification of $v(x)$, so we want to be flexible in our specification of $v(x)$. To avoid problems due to misspecification of the value function we estimate a separate value function for each of the two amounts. Each value function is specified as follows: $v(x) = x^{\alpha}$, $x \geq 0$, $-\lambda(-x)^{\alpha}$, $x < 0$. We allow the parameter λ to be different for the two value functions.[5] Our data do not permit us to estimate different powers for the gain and loss segment of the value function, so we restrict them to be the same. Since Tversky and Kahneman (1992) find the same power for the gain and loss segment in their empirical application, this assumption is likely to be harmless.

We now turn to some identification issues. It is well known that the scale of a utility function or a value function is not identified. Given the multiplicative nature of the model under consideration this is not the only feature of the value function that is not identified with the data we have. Neither the general curvature of the value function, nor the level of discounting is identified. This can easily be seen by the fact that if the general model presented in Table 5.3 holds for a certain $v(x)$ and $\phi(t)$, then also the model with $v^{*}(x) = v(x)^{\gamma}$, $x \geq 0$,

[5] The fact that different amounts result in different discount rates is evidence that the power specification itself does not hold for the actual value functions. We use two different value functions with the power specification to approximate the actual value function.

Table 5.4: Predictions for the answers from the model.

Scenario	Model prediction
Delay receipt	$P = \frac{\lambda - \phi}{\phi} \cdot m$
Delay payment	$P = \frac{1 - \phi\lambda}{\phi\lambda} \cdot m$
Speed up receipt	$P = 1 - \phi\lambda \cdot m$
Speed up payment	$P = \frac{\lambda - \phi}{\lambda} \cdot m$

$v^*(x) = -(-v(x))^\gamma$, $x < 0$, and $\phi^*(t) = \phi(t)^\gamma$ will be observationally equivalent for every γ. So, the value of α and the discount factor are not identified. This identification problem is not typical for our model, but is present in all the research on time preference we know.[6] To estimate our model we have to make some normalization. We use the normalization that is almost always implicitly used in the literature, which is $\alpha = 1$, implying that the value function is piecewise linear. When interpreting our results we will come back to this issue.

Using the specification of the discount function and the approximation for the value function we present the predictions for the answers, P, in terms of our model for each scenario in Table 5.4. ϕ denotes the discount factor that is relevant for the time delay of the question and λ denotes the loss aversion parameter for the relevant amount, which is likely to be larger than one. Finally, m denotes the relevant amount of money for the question.

The model has a total of four individual specific parameters, which are two discount factors, one for each delay length, and two loss aversion parameters, one for each amount. These individual specific parameters vary across respondents with a set of observed demographic characteristics such as the respondent's age, income, education, gender, employment status, and family size. Precise definitions and some descriptive statistics of these variables are given in Appendix 5.B. The individual specific parameters in the model are parameterized using a number of parameters that have to be estimated. For each discount factor and also for each loss aversion parameter in the model we use one auxiliary parameter indicating the level. These parameters for the level will then be adjusted using the observed demographic variables to obtain the individual specific parameters.

[6] The problem can be solved using questions with outcomes at more than two points in time, but these questions are difficult to answer. The quality of the data is likely to suffer from this, especially when one uses a representative sample for the whole population.

An example is the one year discount factor for individual i, ϕ_i^{12}, which is modelled as $\phi^{12} \cdot \exp(x_i'\beta_\phi)$. Here ϕ^{12} is the parameter for the level of the one year discount factor and β_ϕ is a vector of parameters controlling for the influence of the observed characteristics. The vector x_i contains the observed demographic variables measured as deviations from their sample averages. In this way the level parameter approximates the average of the individual specific parameters. The parameters in β_ϕ then indicate what the effect of the individual characteristics is on the discount factor. The value of the index $x_i'\beta_\phi$ can be interpreted as a measure of patience for individual i. Higher values of $x_i'\beta_\phi$ imply higher discount factors and thus lower discount rates. For the three months discount rate we use the same index, but allow it to have a different effect as follows: $\phi_i^3 = \phi^3 \cdot \exp(\gamma_3 x_i'\beta_\phi)$, with γ_3 a scalar.[7] A similar parameterization is used for the loss aversion parameter, where $\lambda_i^H = \lambda^H \cdot \exp(x_i'\beta_\lambda)$ and $\lambda_i^L = \lambda^L \cdot \exp(x_i'\beta_\lambda)$, where the superscripts H and L indicate the loss aversion parameter for the high and low amount of money respectively. A positive (negative) value of the index $x_i'\beta_\lambda$ then indicates that individual i is more (less) loss averse than the average individual. This way of modelling the individual specific parameters in the model allows us to focus on both the predictions for the average individual and the variation across individuals.

It is not very likely that the demographic variables pick up all the heterogeneity across individuals. To capture this unobserved heterogeneity across individuals we add random effects to the model. To allow for unobserved heterogeneity in both the discount rates and in the level of loss aversion we specify two random effects, one for the discount rate and one for the level of loss aversion. The two random effects are independent of the other observed characteristics and have a joint discrete distribution with two mass points,[8] similar to the ideas presented in Heckman and Singer (1984). A mass point of the random effects distribution, RE_k, is defined as $(RE_k^\phi, RE_k^\lambda)$. The first component, RE_k^ϕ, influences the discount rates in the same way as the explanatory variables and is thus added to the index $x_i'\beta_\phi$. The second component, RE_k^λ, influences loss aversion in a similar way and is added to $x_i'\beta_\lambda$.

[7]This approach allows the equality $\phi_i^{12} = \left(\phi_i^3\right)^4$ and thus exponential discounting to hold exactly for each individual.

[8]With more than two mass points the estimation algorithm did not converge.

We use the individual specific parameters defined above to obtain predictions of the answers to the questions according to the formulas in Table 5.4. Since the individual specific parameters also depend on the random effects, we can only obtain predictions conditional on the random effect. Let P_{ik}^{q} denote the prediction of individual i's answer to question q, given random effect k, and y_i^q denote individual i's answer to question q then the difference between individual i's answer and the prediction is modelled with an error term, so $\varepsilon_{ik}^{q} = y_i^q - P_{ik}^{q}$. This error term, ε_{ik}^{q}, is assumed to be normally distributed and independent across individuals and questions. Heteroskedasticity with respect to differences in age and gender is also allowed for by setting the standard deviation of the error terms proportional to $\exp(z_i'\delta)$, where z_i is a vector containing age and gender, measured as deviations from their sample means, and δ is a vector of parameters that has to be estimated.

The model predictions, allowing the random component, can become negative. However, the questionnaire did not allow for negative answers and respondents that would have had a negative value are asked to fill out zero. We take this into account in our model using a Tobit type specification for each question (see Amemiya (1985)). We estimate the model using maximum likelihood. The likelihood function of the model is presented in Appendix 5.C.

5.5 Estimation results

The empirical model is estimated using the answers to the questions with an amount of Dfl 1,000 and Dfl 100,000 jointly[9] and separately to see whether there are differences in discount rates between these two amounts, as is suggested in, for example, Green et al. (1997).

Table 5.5 presents the estimates for the level of loss aversion and the discount rates, r^3 and r^{12}, that correspond to the discount factors, ϕ^3 and ϕ^{12}, in the model. The observed demographics we incorporated into x_i, the vector of explanatory variables, and their effect on the discount factors and the level of loss aversion are presented in Table 5.6. We start with a discussion of the estimates presented in Table 5.5. The estimated average discount rates are significantly negative,

[9]We use all the questions, but still approximate the actual value function using separate value functions for each amount.

Table 5.5: Parameter estimates, standard errors in parentheses.

Parameter	Both amounts	Only Dfl 1,000	Only Dfl 100,000
r^3	-0.015 (0.001)	-0.049 (0.003)	-0.005 (0.001)
r^{12}	-0.010 (0.002)	-0.015 (0.003)	-0.002 (0.002)
λ^L	1.042 (0.001)	1.048 (0.002)	——
λ^H	1.013 (0.001)	——	1.016 (0.001)

except for the estimates using only the high amount questions, where the one year discount rate is negative but insignificant. Our estimates for the two amounts separately confirm the observation of Green et al. (1997) that individuals are more patient when higher amounts of money are concerned. Our results for the discount rates are in sharp contrast with the conclusions from previous studies, where data with similar characteristics were interpreted as evidence for very high discount rates, based on the high average discount rates as presented in Table 5.2. One of the reasons why the implied discount rates we find are also smaller than in previous studies is that the questions we use give individuals the possibility to answer zero. The reference dependent model actually predicts negative answers if the level of loss aversion multiplied by the discount factor is larger than one. In some of the previous studies, questions are used in which it was impossible to state such preferences and respondents might have been forced to give answers that did not represent their true preferences.

The estimates for λ^L and λ^H are significantly larger than one, indicating that there is loss aversion. The estimates indicate that the disutility of a loss is only a few percent higher than the utility of an equally sized gain. The level of loss aversion in the type of riskless choice situations we consider here turns out to be completely different from the level of loss aversion found in decision making under risk, where λ is estimated to be around 2.5, as in, for example, Tversky and Kahneman (1992). An explanation for this is the fact that in intertemporal choices loss aversion is concerned with giving up something, while at the same time knowing that one will get something back in return. In risky choices, however, loss aversion is related to the possibility of loosing something for the possibility of winning something else. If, however, ex post the loss turns out to be relevant and one did not receive anything in return for it, the decision maker may feel regret. If this regret is anticipated, this can make the loss harder to bear ex ante. This can explain why the magnitude of loss aversion in risky choice situations, where it may be combined with regret, is larger than in riskless choice situations.

The estimation results presented in Table 5.5 depend on the normalization $\alpha = 1$. In the situation with a value function with diminishing marginal sensitivity, α is smaller than one. If this is the case then the estimates for the discount factors and the levels of loss aversion are biased away from 1, which means that the level of loss aversion is smaller than we estimated and that the discount rates are closer to zero. If we want to compare the parameter estimates for the two amounts separately, we have to be careful since the normalization does not need to have the same effect in the two situations. The differences between the estimated discount rates in the second and third column, however, are rather large, making an explanation of this difference based on a different effect of the normalization implausible.[10]

Table 5.6: Estimates for β_ϕ and β_λ.

Variable	ϕ	λ
Age	0.358 (0.040)	-0.043 (0.003)
Female	13.278 (1.028)	-0.044 (0.060)
Married	-5.618 (1.031)	-0.085 (0.073)
Employed	-3.164 (0.622)	0.094 (0.064)
Education	0.061 (0.293)	-0.041 (0.019)
Family size	0.152 (0.340)	-0.019 (0.020)
Log(income)	1.939 (0.622)	-0.113 (0.041)
Dinczero	14.412 (4.768)	-0.924 (0.310)
γ_3	0.592 (0.026)	

Table 5.6 presents the estimated coefficients for the effect of the observed individual characteristics on the discount factors and the level of loss aversion. The estimates are calculated using all the questions. The estimation results for the high and low amount separately are comparable. All coefficients are scaled

[10]The effect of the normalization is that we estimate ϕ^{1/α^*}, where α^* is the actual power in the value function. Different α's for the two amounts thus result in a difference in the ratio of the logs of the estimated values. Estimates of the ratio of the two α's under the assumption that ϕ is constant can be obtained from $\log(1.049)/\log(1.005) = 9.6$ and from $\log(1.015)/\log(1.002) = 7.5$.

with a factor 1000.

The annual discount factor that is used by males, is thus ,*ceteris paribus*, $\exp(13.278/1000) = 1.3\%$ smaller than the discount factor used by females. Since the discount factors are close to one, the discount rate used by males is about 1.3% points higher. Younger individuals are less patient than older people, where a difference of ten years affects the discount rate with 0.4%. Income is also significant with the higher incomes related to lower rates of time preference. This can be due to a direct effect of income, which allows individuals to satisfy more of their needs, making them more patient. It can also be due to the fact that more patient individuals have invested more in their education and earn more for that reason. The *ceteris paribus* effect of education itself, however, is insignificant. Furthermore, individuals that are married and have a job are less patient. These effects are small but significant. Our results extend the results of Green et al. (1994) and Green et al. (1996), who report negative effects of age and income on observed discount rates. In these studies, however, only a small number of subjects are used and there was no control for other characteristics, while our results show that especially gender plays a very important role.

From the estimates for β_ϕ and the random effects we can conclude that there is substantial variation in the individual specific discount factors. The three month discount factor, ϕ_i^3, varies between 0.978 and 1.105, while ϕ_i^{12} varies between 0.949 and 1.165. The random effect is included by simulating draws from the random effects distribution. The variation due to the random effect is substantial.

Testing for exponential discounting can be done in two ways. Using a likelihood ratio test we can test whether $\phi^{12} = \left(\phi^3\right)^4$. This test strongly rejects the hypothesis that exponential discounting holds. A second way of testing for exponential discounting is to look at the effect of the individual variation across individuals. Under the hypothesis of exponential discounting $\gamma_3 = 0.25$ should hold. This is also clearly rejected by the data. Note that the concept of hyperbolic discounting is difficult to understand if individuals do not have positive discount rates. Our results, however, do not support the underlying idea that the annual discount rates used to discount outcomes in the near future are larger than the discount rates for outcomes further away in time.

The estimation results for β_λ show that there is a significant positive effect of age on the level of loss aversion, while income and the education level have a negative effect on loss aversion. These effects result in a variation of λ^L between 1.038 and 1.044. The economic importance of this variation is small.[11]

Estimation results for the parameters of the error distributions for the scenarios and for the random effect are presented in Appendix 5.D. It is worthwhile mentioning that the random effect for the discount factors and loss aversion are negatively correlated, indicating that with respect to the unobserved heterogeneity more loss averse individuals are also less patient, on average. The same holds for the observed heterogeneity, since $x_i'\beta_\phi$ and $x_i'\beta_\lambda$ are also negatively correlated.

The estimates resulting from the model show mainly negative rates of time preference and small levels of loss aversion. To see whether these unexpected outcomes actually give a good description of the data we compare predictions from the model with the actual data. In the predictions we take into account the random components by simulating draws from the random effects distribution and from the distribution of ε_i^q. We look at both the number of zeroes predicted by the model and the mean of the implied discount rates for each question. We use the parameter estimates obtained using all the questions. Calculation of prediction intervals is very difficult given the estimation uncertainty and the nonlinearity of the model. For this reason we only report the predictions of the sample averages in Tables 5.7 and 5.8.

Table 5.7: Comparison of the data and model predictions:
The fraction of individuals answering zero

	Actual data				Model predictions			
	delrec	*delpay*	*sperec*	*spepay*	*delrec*	*delpay*	*sperec*	*spepay*
H12	0.141	0.570	0.590	0.390	0.489	0.537	0.542	0.470
H3	0.194	0.614	0.676	0.391	0.499	0.679	0.678	0.485
L12	0.180	0.675	0.705	0.392	0.443	0.643	0.656	0.409
L3	0.336	0.766	0.817	0.418	0.423	0.737	0.784	0.365

[11] The interpretation of these estimation results depends on the normalizing assumption that $\alpha = 1$. It is, however, not too difficult to imagine that α also varies with some observed characteristics. Some ideas about correcting for the assumption $\alpha = 1$ can be obtained from Chapter 4. We did not use the lottery questions when we estimate the model, since they do not solve the identification problem. See the discussion of the identification issues in that chapter.

Table 5.8: Comparison of the data and model predictions:
The average implied discount rates including zeroes

	Actual data				Model predictions			
	delrec	*delpay*	*sperec*	*spepay*	*delrec*	*delpay*	*sperec*	*spepay*
H12	0.129	0.019	0.020	0.062	0.081	0.024	0.026	0.054
H3	0.050	0.008	0.007	0.027	0.040	0.007	0.008	0.026
L12	0.197	0.030	0.025	0.106	0.118	0.029	0.028	0.088
L3	0.075	0.016	0.008	0.049	0.068	0.013	0.009	0.055

When we compare the predictions from the model with respect to the number of zeroes, we see that the model has some difficulties in explaining the small number of zeroes for the *delrec* scenario. It is, however, able to explain the large number of zeroes for the *delpay* and *sperec* scenarios. If we turn to the comparison of the mean discount rates we see that the model has a remarkably good fit to the average discount rates in the data. This shows that, although implied discount rates vary substantially between questions, this can still be very well explained using a simple model with scenario independent parameters.

5.6 Conclusions

This chapter quantifies the different aspects of the intertemporal choice model proposed by Loewenstein and Prelec (1992). Their model explains a number of anomalies that have been found in numerous experiments in the past. These anomalies are based on differences between implied discount rates between different scenarios and the differences between different delay lengths and amounts of money involved.

The data we use come from a large Dutch household survey. The questionnaire contains a set of questions on time preference that vary with respect to four dimensions: delay or speed up, gain or loss, two amounts of money, and two time spans. This results in 16 possible settings, which are all asked to each respondent in the survey. The resulting mean implied discount rates from the answers given by the respondents to the questions confirm the patterns found in previous studies.

The discount rates implied by the answers are, in general, very high and the traditional interpretation is that this is due to high levels of time discounting. Our estimation results, however, show that the joint effect of loss aversion and time preference is capable of generating large differences between the scenarios, while, at the same time, each effect is rather small of its own. Our estimation results show that the level of loss aversion is small and discount rates are negative. To check whether this rather counterintuitive result makes sense we confronted predictions of our model with the data: it turns out that the model fits the average implied discount rates quite well. The problem with previous experiments might be that the data have been interpreted in terms of the mean implied discount rates, which can be very sensitive to outliers, especially in case of a skewed distribution of answers as in our case.

We also investigated the relationship of the level of loss aversion and the discount factors with other observed characteristics, such as age, gender, and income. Our results indicate that there is substantial and predictable variation of discount rates across individuals. On average females and older people are more patient; also income is positively related to patience. This information can be useful for banks that want to know which individuals are more likely to save, but it can also be very useful for a government to know which parts of the population are less patient. The government could, for example, direct long term savings plans specifically to these groups of individuals.

The results presented in this chapter give a different look at the anomalies that have been found in the literature on time discounting. They point at many new aspects of time preference and loss aversion, that were previously unknown. We have shown that using a structural model for the individual decision making process can result in new insights. It also allows one to predict the decisions that are made in different situations, which is not possible with reduced form models. This approach can also be fruitfully applied in other areas of individual decision making.

5.A Questions for the scenarios

Delay payment scenario

Imagine you receive an assessment for tax arrears of Dfl 1000. You get the option to pay 3 months later.

What amount of money would you be willing to pay at most extra for delay the payment with three months? If you are not interested in the delay of payment or you are not willing to pay any extra money, you can fill out 0.
At most extra Dfl ....

Speed up receipt scenario

Imagine you receive a message from the Staatsloterij that you won a prize of Dfl 1000. The money will be paid in three months time. It is, however, possible to receive the money right now, but in that case you receive less than Dfl 1000.

With at most how much less would you agree if you would receive the money three months earlier. If you are not interested in early payment or you are not willing to give up any money, you can fill out 0.

At most Dfl ....

Speed up payment scenario

Imagine you receive an assessment for tax arrears of Dfl 1000. This money has to be paid in three months time. It is, however, possible to pay the money immediately. In this case there is a reduction of the amount of money you have to pay.

How much reduction do you want at least to pay the assessment immediately? If you are not interested in such a reduction or if you do not need a reduction to pay immediately, you can fill out 0.

At least a reduction of Dfl ....

5.B Data

Table 5.9: Descriptive statistics for the observed individual characteristics

Variable	Mean	Std. Dev.	Description
Age	50.0	13.0	Age of respondent
Female	0.544	0.498	Dummy; 1 if female
Married	0.848	0.359	Dummy; 1 if married
Employed	0.604	0.489	Dummy; 1 if employed
Education	2.866	1.301	Education level, 3 levels (1,3, and 5)
Family size	2.794	1.325	Family size
Log(income)	7.836	0.760	Log(net annual income)
Dinczero	0.179	0.384	Dummy; 1 if income is not observed

5.C The likelihood function

The likelihood function of the whole model is rather complicated and will, therefore, be introduced in a few steps. First of all we have a joint likelihood for a random sample of N individuals. The likelihood as a function of the parameters, θ, looks as follows:

$$L(\theta) = \Pi_{i=1}^{N} L_i(\theta). \tag{5.1}$$

For each individual we have Q questions and we allow for correlation in the random components in the model through the random effects with a discrete distribution with K mass points. For each individual the function $L_i(\theta)$ can thus be written as follows:

$$L_i(\theta) = \Sigma_{k=1}^{K} \left[\Pi_{q=1}^{Q} L_i^q(RE_k) \right] \cdot P(RE = RE_k). \tag{5.2}$$

For notational convenience we do not specify explicitly what the parameters are that we estimate, so all quantities mentioned can depend on the parameters, θ, without explicit reference to it. In (5.2) $P(RE = RE_k)$ denotes the probability mass attributed to the event that the random effect equals RE_k, which is defined for the K mass points. $L_i^q(\theta; RE)$ is the likelihood for the answer that respondent i has given to question q, given the value of x_i and the random effect. Both the probabilities and the values for the random effects, RE_k, are estimated

For each question q we can use the model predictions presented in Table 5.4 to obtain a prediction, P_{ik}^q, of the answer for respondent i for question q, given that the random effect is RE_k. In the generation of these predictions we have to use the basic parameters adjusted for the observed individual characteristics and the random effect. For example for the questions with a high amount of money and the delay of one year we have to replace ϕ in Table 5.4 with $\phi_i^{12} = \phi^{12} \cdot \exp(x_i'\beta_\phi + RE_k^\phi)$ and λ with $\lambda_i^H = \lambda^H \cdot \exp(x_i'\beta_\lambda + RE_k^\lambda)$. The parameters that we estimate here are ϕ^{12}, λ^H, β_ϕ, and β_λ. Unmentioned, but also estimated are ϕ^3 and λ^L.

If respondents would have had the possibility to give negative answers, the likelihood of observing answer y_i^q from respondent i on question q, given that the random effect equals RE_k, would be $f_{qi}(y_i^q - P_{ik}^q)$, where f_{qi} is the density function of a normal distribution with mean zero and standard deviation σ_{qi}. We allow for heteroskedasticity; the standard deviation depends on some observed characteristics through $\sigma_{qi} = \sigma_q \cdot \exp(z_i'\delta)$ Here δ and σ_q, $q = 1, \ldots, Q$, are parameters that are estimated.

Since the respondents have to answer nonnegative amounts the appropriate specification of $L_i^q(\theta, RE_k)$ is the following:

$$L_i^q(\theta, RE_k) = f_{qi}(y_i^q - P_{ik}^q) \cdot I(y_i^q > 0) + F_{qi}(-P_{ik}^q) \cdot I(y_i^q = 0), \tag{5.3}$$

with F_{qi} denoting the normal distribution with variance σ_{qi}^2 and mean zero.

5.D Estimation results stochastic specification

Table 5.10 reports the estimated values of σ_q for the different scenarios.

Table 5.10: Estimates for the scenario specific standard deviations of the random disturbances (standard errors in parentheses).

Scenario	Amount and time	Standard deviation of random error
delrec	*L3*	126 (1.30)
	L12	237 (3.11)
	H3	9130 (60.5)
	H12	18164 (182.4)
delpay	*L3*	75 (0.86)
	L12	107 (1.40)
	H3	2603 (35.5)
	H12	5473 (65.6)
sperec	*L3*	59 (1.11)
	L12	92 (1.62)
	H3	2861 (54.0)
	L12	5569 (91.2)
spepay	*L3*	71 (0.79)
	L12	117 (1.64)
	H3	4712 (51.4)
	H12	8691 (108.5)

Table 5.11: Estimation results for the parameters in δ (standard errors in parentheses).

Variable	Estimate
Age	-0.012 (0.000)
Female	0.074 (0.004)

Table 5.12: Estimation results for the random effect (standard errors in parentheses).

k	Probability	RE_k^{ϕ}	$RE_k^{\lambda} \times 100$
1	0.725 (0.012)	-0.042 (0.002)	0.058 (0.006)
2	0.275	0.111	-0.153

Note: Standard errors are only reported for one mass point. The estimates for the other mass point are derived from the condition that the mean random effect equals zero.

Chapter 6

First order risk aversion and the stock holding puzzle

In this chapter we investigate to what extent preferences that display first order risk aversion can solve the stock holding puzzle. The importance of this puzzle results from the direct link between the stock holding puzzle and the equity premium puzzle. We focus on optimal portfolio allocations and consumption decisions of individuals with preferences that display first order risk aversion due to the presence of probability weighting or loss aversion. It turns out that probability weighting has a large impact on portfolio choices, where the optimal holdings of risky assets are reduced substantially. Thus probability weighting might solve the equity premium puzzle. The effect of probability weighting on the optimal consumption and savings decisions is small. The reverse holds for loss aversion. It reduces the optimal portfolio weights given to the risky assets slightly, but it has a large impact on the optimal consumption and savings decisions. Individuals that are loss averse build up larger amounts of precautionary savings. A remarkable finding is that they do not dissave after retirement, so loss aversion might be an explanation for the retirement savings puzzle.

6.1 Introduction

The average return on stocks has exceeded the return on safe investments by far in the past decades. Mehra and Prescott (1985) show that a representative agent model with constant relative risk aversion (CRRA) preferences and expected utility is not able to explain such a large gap in returns without implausibly high levels of risk aversion. This unexplained phenomenon is known as the 'equity premium puzzle'. A survey of modifications to the model and proposed solutions to the equity premium puzzle is given by Kocherlakota (1996) in an article with the appropriate title 'The Equity Premium: It's still a Puzzle'. His conclusion is that *we must seek to identify what fundamental features of goods and asset markets lead to large risk adjusted price differences between stocks and bonds.*

The microeconomic manifestation of the equity premium puzzle is the stock holding puzzle, which relates to the fact that many households do not own stocks, even though the expected return on holding stocks is relatively high. This phenomenon is even more remarkable since Pratt (1964) shows that expected utility theory predicts that a decision maker will prefer to own at least a small part of any lottery over not owning it at all, as long as the expected payoff of the lottery is positive and the utility function is twice differentiable. This implies that individuals should own at least some risky assets, if we assume that the expected excess return of risky assets is positive.[1]

In this chapter we try to find specifications of the agent's decision making process that predict optimal portfolio choices that are closer to observed behavior than the traditional specifications. Such preferences can solve the stock holding puzzle and are candidate solutions to the equity premium puzzle. This can be seen from the fact that when the high expected returns on the risky asset result in large demands for the risky asset, it will be difficult to explain the high returns in a general equilibrium model. However, if preferences are such that the stock holding puzzle is resolved, these preferences do not result in high demands for the risky asset. This will make it more likely that the high expected returns can be explained in a general equilibrium model.

Starting point for the preference specifications we consider is the concept of first order risk aversion which is defined in Segal and Spivak (1990). They also explain why preferences with first order risk aversion can be a solution for the equity premium puzzle and the stock holding puzzle. The main idea is that with first order risk aversion the risk premium for a certain risk has to exceed some amount, before an individual is interested in investing in it, while with second

[1] Implicit assumptions here are that the risky asset is infinitely divisible and that individuals own some assets.

order risk aversion Pratt (1964)'s results hold and an investor is always interested in a very small amount.

In the literature on decision making under risk and uncertainty two important phenomena are discussed that both lead to preferences with first order risk aversion. These two phenomena are loss aversion and probability weighting or rank dependent utility, see Tversky and Kahneman (1992), among others. Although most of the research on these phenomena is conducted in the experimental psychology and economics literature, there are also applications to real life decision making, like the savings and investment decisions we are interested in. Probability weighting in a consumption or portfolio choice model is used by, for example, Epstein and Zin (1989, 1990) and Haliassos and Hassapis (2001). Loss aversion is used by Aizenman (1998), Barberis, Huang, and Santos (1999), Benartzi and Thaler (1995), and Bowman, Minehart, and Rabin (1999).

Up to now loss aversion and probability weighting have been treated as two separate solutions to the equity premium puzzle, while the psychological literature, from which both concepts originate, discusses them simultaneously in the context of decision making under risk or uncertainty. We present a general preference specification that incorporates both probability weighting and loss aversion, so we can investigate the merits of each concept separately, but also their joint effect.

We focus on individual decision making, where the individual decides upon his optimal consumption and investment path, taking the distribution of prices and income as given.[2] We do not use a representative agent model, since aggregation of behavior resulting from such preferences is not straightforward. Another reason why it is important to investigate individual behavior when one is interested in saving and investment decisions is that individuals do not live infinitely long and also have life cycle saving motives, like saving for retirement.

Our interest is in the consequences of different preference specifications for optimal consumption and investment decisions. The most important difference between the preference specifications we consider and the one used by Mehra and Prescott (1985) is the presence of first order risk aversion. We specify preferences

[2]We will use both risk and uncertainty to denote the random income and asset return processes, whose probability distributions are assumed to be known. Asset pricing under Knightian uncertainty is discussed in, for example, Epstein and Wang (1994).

with first order risk aversion by incorporating probability weighting, loss aversion, or both in the agent's preferences. The agent makes his decisions in an economy with three sources of uncertainty. The first source is the income uncertainty the individual faces in each period before retirement. After retirement this uncertainty disappears. The second source of uncertainty is lifetime uncertainty and, finally, the return on one of the assets is uncertain.

The agent's life is modelled from the age of 25 to the age of 84. Each year the agent has to decide how much to consume and how much to invest in the risky asset and in the riskless asset. We assume that the agent makes these decisions by maximizing the expected utility of current and appropriately discounted future consumption, where the expectation is taken using decision weights instead of objective probabilities. Optimal consumption and investment decisions are calculated using stochastic dynamic programming techniques (see Deaton (1991) or Hubbard, Skinner, and Zeldes (1995)). We present an example of the optimal consumption and investment rules, but we focus on the behavior of consumption and investment through time by simulating the income and asset return processes and tracking the decisions made by the agent in each period. In this way we characterize both individual and aggregate consumption and investment levels across time.

Our main findings are that adding loss aversion to the model of Mehra and Prescott does not change the optimal portfolio choices substantially. There is, however, a large effect of probability weighting on portfolio choices. Optimal investments in the risky assets are significantly lower. This implies that the high expected return on risky assets is not necessarily in contradiction with the small number of households that own risky assets. There is also an unexpected effect of loss aversion on the savings behavior after retirement. The low dissaving of the elderly is an observed, but also unexplained phenomenon. When we introduce loss aversion into the preference specification, this behavior is predicted by the model, so loss aversion might be a solution to the retirement savings puzzle (see Davies (1981), but also Banks et al. (1998)).

The remainder of this chapter is structured as follows: Section 6.2 discusses the concepts of loss aversion and probability weighting and presents an overview of some related literature. Section 6.3 gives a detailed description of the preference specification and the economic environment. Section 6.4 presents the optimal consumption and investment strategies for a number of different preference specifications that differ with respect to loss aversion and probability weighting. Section 6.6 discusses the implications for the stock holding puzzle and possibilities for further developments in this line of research.

6.2 Overview

On average, stocks returns have been extremely high compared to the return on safe investments, as reported in Mehra and Prescott (1985), among others. They report that the standard deviation of annual stock returns, based on the S&P 500, has been 16.7% over the period from 1889 to 1978, while the average return was 6.18% higher than the return on relatively riskless investments, like 3-month T-bills. Mehra and Prescott (1985) model the implications of these observations with a representative agent model. The representative agent maximizes his expected discounted utility of future consumption, where the utility from consumption is of the constant relative risk aversion (CRRA) type. Given the stochastic properties of average per capita consumption, they derive the behavior of equilibrium asset prices over time, which depends on the preferences chosen. In order to explain the observed equity premium a level of constant relative risk aversion of about thirty is needed, which is generally considered to be implausibly high. Individual behavior that is implied by the model used by Mehra and Prescott is studied extensively in Hochguertel (1998) and in Cocco, Gomes, and Maenhout (1999).

The preference specifications used by Mehra and Prescott have the property of second order risk aversion, as it is defined by Segal and Spivak (1990). With second order risk aversion, the risk premium for a risky investment, i.e., the expected payoff of the risky investment, that an individual requires to be indifferent between holding the risky asset and not holding it, is proportional to the variance of the investment, while first order risk aversion implies that this risk premium is proportional to the standard deviation of the return of the investment. If individuals' preferences are risk averse of order two, they will hold at least a small amount of risky assets in the absence of transaction or other fixed costs. However, if preferences are risk averse of order one this is not necessarily true. First order risk aversion might thus explain the empirical finding that many households do not own any risky assets. In the remaining part of this section we discuss some characteristics of the preference specification of Mehra and Prescott and indicate how we can modify their preference specification to obtain preferences with first order risk aversion. We also present an overview of the existing literature on consumption and investment decisions that uses preferences with first order risk aversion.

One of the most important paradigms used in the structural analysis of economic decision making, which is also used by Mehra and Prescott, is the expected utility paradigm, see von Neumann and Morgenstern (1947). However, the descriptive validity of expected utility has been a point of discussion since Allais (1953). By now a large body of evidence has been accumulated questioning the empirical validity of the expected utility paradigm, see, for example, Kahneman, Slovich, and Tversky (1982) or Machina (1987). In reaction to this evidence, numerous theories have been proposed, mainly in the experimental psychology literature, that take into account many of the typical violations against expected utility preferences. The preference specification we propose is based on one of these generalizations, which is Cumulative Prospect Theory (CPT, Tversky and Kahneman (1992)). Harless and Camerer (1994) show that CPT is a useful theory, since it explains a large part of the anomalies, while at the same time the total number of different types of behavior that can be explained with CPT remains limited.

Cumulative Prospect Theory is different from Mehra and Prescott's model in two respects. The first difference is that outcomes are evaluated with a reference point dependent value function. This means that the value attributed to an outcome depends not only on the outcome, but also on the reference level. An example of a reference point dependent value function is presented in Figure 6.1. The reference point in this figure is the zero outcome. Outcomes below the reference point (negative values in the figure) are called losses, since they are experienced as such, while outcomes above the reference point are referred to as gains. The results of numerous experiments indicate that the utility of a gain is smaller than the disutility of an equally large loss. The reason for this is that individuals do not like to give up something they have, i.e., they do not like to lose something. This phenomenon has received the name loss aversion and is not only observed in risky choices, like the choices between lotteries studied in

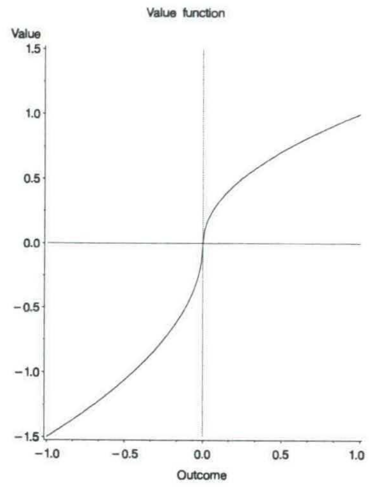

Figure 6.1: A reference point dependent value function.

Chapter 4, but also in intertemporal choice situations, such as the intertemporal choices analyzed in Chapter 5. The main consequence of loss aversion is that it induces a *status quo* bias: individuals, in general, do not like changes. The value function in Figure 6.1 also displays loss aversion, which can be seen from the fact that $v(x)$, the utility of gaining x, is smaller than $-v(-x)$, which is the disutility of losing x.

The second difference between the preference specification used by Mehra and Prescott and CPT is that expected values are computed using decision weights. These weights are derived from a transformation of the objective outcome distribution and are not necessarily equal to the objective probabilities. This is called probability weighting. This phenomenon has been widely studied in decision making under risk in static situations, see, for example, Gonzalez and Wu (1999). Generalizing probability weighting to a dynamic context, however, can lead to dynamic inconsistency, as is discussed by Sarin and Wakker (1998). The problem is that the weights given to future situations vary over time if one attributes decision weights to future consumption paths. Epstein and Zin (1990) overcome this problem by using probability weighting within a recursive utility context (Kreps and Porteus, 1978). Here the future path of consumption is reduced to a one dimensional 'certainty equivalent'. The decision weights are then constructed using the distribution of this certainty equivalent and the problems with dynamic inconsistency are circumvented. Both probability weighting and loss aversion result in first order risk aversion and thus provide possible solutions for the equity premium puzzle.

In this chapter we investigate the optimal consumption and investment decisions of economic agents when these agents have preferences with loss aversion and probability weighting. We consider a large number of preference specifications. Special cases will be the model without loss aversion and probability weighting, which is the model of Mehra and Prescott, but more important is the preference specification that combines loss aversion and probability weighting, which has not been used in this context before. The magnitude of loss aversion and the type of probability weighting are also varied. Before going into detail about the preference specifications, we give an overview of the preference specifications that have been developed and used in the literature on saving and investment decisions and in the literature on the equity premium puzzle.

The concept of loss aversion can only be used if there is a reference point, with which the outcomes can be compared. The inclusion of reference points in economic decision making is certainly not new. Many different ways exist in which one can model a reference point. Duesenberry (1949) presented evidence of a reference effect of the group an individual lives in. Reference points, however, can also depend on the individual's past. In the literature on habit formation the current habit, which can be seen as a reference point, depends on past consumption levels. However, there is one difference between models with habit formation as they are usually used and a model with reference dependence and loss aversion. In models with habit formation it is, in principle, possible to consume below the level of the habit, see Deaton (1992), but in many applications this is not considered or it yields an infinitely negative amount of utility, like in Alessie and Lusardi (1997) and in Campbell and Cochrane (1999). In our model it will be crucial that individuals can consume below their reference level.

Bowman, Minehart, and Rabin (1999) follow the literature on habit formation when they specify the dynamics of the reference point for the level of consumption. The reference point thus depends on past levels of consumption. They use a preference specification for consumption that is based on CPT and displays loss aversion. They extend the work of Tversky and Kahneman (1992) by using a reference point that is endogenously determined, but they also need to impose restrictions on the derivatives of the value function. Without these restrictions the optimal consumption path will be to save as much as possible until the last period and then consume everything. This does not seem realistic, at least, not as a general solution of the problem. Generalizing this setting to more periods will strengthen the restrictions needed on the value function if one uses a CPT type value function. The economic problem they study is the consumption and saving decision in a two period model with income uncertainty. They do not include a portfolio choice.

Loss aversion is also applied in Benartzi and Thaler (1995). They take the preference specification and the parameter estimates from Tversky and Kahneman (1992) and use these preferences to explain the equity premium puzzle by assuming that utility is based on asset returns at the moment one evaluates the asset portfolio. The question they answer is which evaluation horizon is compatible with the observed equity premium. With the zero return situation as the reference point they conclude that a yearly evaluation of portfolio performance is consistent with the observed equity premium. Their model is generalized to a dynamic setting, including a consumption and investment decision in Barberis, Huang, and Santos (1999). These latter authors use the representative agent model of Mehra and Prescott (1985) and add the preference specification of Benartzi and Thaler (1995), defined over end of period wealth. This does not yield satisfactory results, but when they take into account some effects of past gains on current utility, the results become more satisfactory. However, it is hard to justify a preference specification of a representative agent based on evidence from individual behavior without a discussion of the aggregation issues. Especially aggregation with reference points and kinked utility functions is difficult if there is heterogeneity with respect to the reference point. Aggregation of utility functions with multiple reference points will result in an average utility function with multiple smaller kinks.[3]

Probability weighting is applied by Epstein and Zin (1990) in a representative agent model. They derive the distribution of equilibrium asset returns, which they compare with the empirical distribution of asset returns. Again, it seems

[3]When individuals' reference points have a continuous distribution, the average utility function even converges to a smooth utility function when more and more individuals are aggregated.

more sensible to look at aggregate behavior of individuals having this type of preferences than taking a representative agent with these preferences without discussing aggregation aspects. This is done in Haliassos and Hassapis (2001), who take the preference specification of Epstein and Zin (1990) and compute optimal investment and consumption behavior of individual agents in a three period model, where income is stochastic in the second period. They do not incorporate loss aversion into the preference specification. With respect to the specification of the environment the major differences are that we incorporate lifetime uncertainty and allow for income uncertainty in more than one period, making the analysis more realistic.

Also related is the paper by Aizenman (1998) on optimal saving in a two period consumption model. He starts with Gul's (1991) disappointment aversion model, where the reference point is endogenously determined by the certainty equivalent. This type of models is very difficult to solve once we allow for investment decisions. The reference point will be dependent on the investment decision and the investment decision depends on the reference point. In our model the reference point is also determined endogenously, but it depends only on the past. Each time a decision has to be made, the reference point is thus already known. This makes the model easier to solve.

6.3 Model specification

In this section we describe and motivate the specification of the individual preferences and the economy in which the individual lives. We also present some details of the solution method used to compute the optimal decisions of the individuals.

The economy

The individuals live in a world where consumption goods are supplied at a unit price. Individuals earn an uncertain income during their working life and have a known retirement income after age 65. With this income and their financial assets they can buy the consumption good or invest in two traded assets. One of these two assets, the risk free asset, yields a risk free return, r, while the other asset, which we call the risky asset, in each period has a normally distributed stochastic return, $\tilde{R}$, with a known mean and variance. For notational convenience we also define the excess return, R, which equals $\tilde{R} - r$. For the relevant magnitudes of the parameters we use the values presented in Mehra and Prescott. The annual risk free rate equals 0.8%, the equity premium is 6.18% on a yearly basis and the standard deviation of annual stock returns is 16.7%.

We investigate the consumption and portfolio choice decisions of individuals from the age of 25. The individuals we consider have an uncertain lifetime, but do not live beyond the age of 84, so we model 60 years, which comprises most of the working age and a substantial part of the retirement period. The age dependent survival probabilities, $S(t)$, are presented in Appendix 6.A. In each year, t, in which the individual is alive, he receives an income, y_t, chooses a consumption level, c_t, and decides on the amounts to invest in each of the two assets.

Observed individual incomes have a few stylized facts we would like to incorporate into our specification of the economy. One of the important features of individual income is that it has, on average, a hump shaped pattern over the life cycle. Income is generally low for younger individuals, rising until the age of about fifty and lower again in retirement. This property is very important for savings and investment decisions. With respect to the variation in the income process across individuals it is well known that for an individual earning below average in a certain period, it is more likely that he will earn below average in the next period than for an individual currently earning an above average income: shocks in the income process are persistent over time. Finally, there is also variation in income that is only relevant for one period and does not influence income in other periods. This component of income variation is what we call transitory income.[4]

We model the individual income process using two discrete income states[5] and a state dependent continuous income distribution. The discrete income states are denoted with I_t and represent the persistent shocks in the income process The state dependent continuous distributions are used to model the transitory shocks. In each period of their working life the individuals find themselves in

[4]We decompose the income shock into a permanent and a transitory part. This should not be confused with the usual definition of permanent income, which relates to average lifetime income.

[5]Of course more states can result in a better specification of the income process, but this comes at a very large cost in computational time when we solve the model.

one of the two states of the income process, which we refer to as the high and low income state. Conditional on the income state, the individual's income is normally distributed with either a high or a low mean. The standard deviation of this distribution is assumed to be proportional to the mean. In this way the transitory shocks to the income level are proportional to the conditional mean, so in the low income state the transitory shocks are, on average, smaller than in the high income state.

The discrete income state, I_t, follows a first order Markov process. This means that the probability that the individual's income state is different in the next period is constant across periods and independent of the past and of the current income state. The persistence of the shocks in the income process depends on the transition probabilities from one income state to the other. The hump shaped life cycle income profile is incorporated into the specification by having mean income varying with age. In retirement there is no income uncertainty and income only depends on the individual's age.

Although the income process at first sight looks restrictive, it can capture both transitory and persistent income shocks. Furthermore the level of persistence in the income shocks can be varied and we are also able to incorporate the hump shaped life cycle income profile. We base the parameterization of the income process on estimates reported by Hubbard, Skinner, and Zeldes (1995) for high school graduates. A detailed description of the parameterization is given in Appendix 6.A.

With respect to the asset market we assume that short sell restrictions apply for both the risky and the riskless asset. This means that individuals cannot borrow money to invest in the stock market or sell stocks they do not own. The total level of assets invested at the end of the period is denoted with A_t. With $\theta_t \in [0,1]$ denoting the fraction of total assets invested in the risky asset, the return on the portfolio of assets will be $(1 + r + \theta_t R)$. The budget constraint for each period can now easily be written down as follows:

$$(1 + r + \theta_{t-1} R) A_{t-1} + y_t = c_t + A_t. \tag{6.1}$$

The amount on the left hand side will be referred to as the amount of cash on hand. It consists of income in the current period and the current value of the investments made in the previous period. The amount of cash on hand is the amount of money the individual has available in the period. It has to be divided between consumption and investments for the next period.

Preferences

The preferences we use in this chapter are different from the more traditional preferences, since they display first order risk aversion instead of second order risk aversion. We discuss the two most important differences between the expected utility model with constant relative risk aversion utility, which is used by, for example, Mehra and Prescott (1985), and the more general preference specification we consider. The new aspects of our preference specification are loss aversion and probability weighting, which both result in first order risk aversion. The two aspects are discussed separately.

First, we present the specification of the utility function, which incorporates loss aversion. We assume that the reference level of consumption in a given period is the consumption level in the previous period.[6] The utility of consumption in period t, c_t, thus depends on the level of consumption in period $t-1$, c_{t-1}. We denote the utility of consuming c_t given c_{t-1} with $U(c_t, c_{t-1})$ and define it as follows:

$$U(c_t, c_{t-1}) \equiv (1-w) \cdot u(c_t) + w \cdot v(c_t - c_{t-1}).$$

Here $u(c_t)$ is the familiar CRRA utility function, $u(c_t) = \frac{c_t^{1-\rho}}{1-\rho}$, where ρ is the level of constant relative risk aversion. This is also the utility function used by Mehra and Prescott (1985). The CRRA utility function is weighted with a weight, $(1-w)$. The remaining weight,[7] w is given to the CPT type value function, $v(c_t - c_{t-1})$. This value function has as its argument the difference between current consumption and consumption in the previous period, which is the reference level of consumption. The function $v(x)$ is the CPT value function, defined as $v(x) = x^{\alpha}$, $x \geq 0$ and $-\lambda(-x)^{\alpha}$, $x < 0$. This CPT value function is the one presented by Tversky and Kahneman (1992), which was also used by Benartzi and Thaler (1995), among others. There are two parameters in the

[6] Other possibilities include, among others, a weighted average of past consumption levels.

[7] This weight is not related to the decision weights given to outcomes in the decision weighting process.

CPT value function, α and λ. The parameter α controls the curvature of the CPT value function and λ is the level of loss aversion in the CPT value function. The parameter λ, however, is not a good measure of the level of loss aversion of $U(c_t, c_{t-1})$, since $U(c_t, c_{t-1})$ also incorporates the CRRA utility function.

The usual definition of the level of loss aversion is the ratio of $-v(-x)/v(x)$, for positive x. In our case, however, such a definition is not possible if we take the consumption level for x, since we cannot have negative consumption. A useful definition of loss aversion with respect to consumption is the difference in utility between consuming a certain percentage, say ε%, less than the reference level for consumption and consuming the reference level itself divided by the difference in utility between consuming ε% more than the reference level for consumption and consuming the reference level itself. This amount still depends on the reference level of consumption. We define the level of loss aversion for $U(c_t, c_{t-1})$ as the ratio presented above evaluated at a reference level that is equal to average lifetime income. We denote the level of loss aversion, according to this definition, with LA, where we take $\varepsilon = 5$, so we look at 5% changes in consumption.

Bowman, Minehart, and Rabin (1999, BMR in the sequel) also use the CPT value function in a consumption and saving model, but without a portfolio choice decision. Their utility function also consists of two parts. The first part attributes utility to the level of the reference point, while the second part is the CPT value function as it is described above. The major advantage of our specification over the specification used by BMR is that they need to impose restrictions on the derivatives of the CPT value function, while this is not the case with our specification. The restrictions they have to impose are difficult to verify and need to be strengthened when the number of periods is extended. They impose these restrictions, because, otherwise, it will be optimal for the agents to save everything until the last period and then consume everything. This type of behavior does not seem very realistic.

The motivation for our preference specification is not different from previous research dealing with consumption and savings behavior. Some researchers prefer traditional time separable utility functions with decreasing marginal utility. Others prefer models with habit formation, where consumption is evaluated relative to some benchmark. However, both the level of consumption per se and the level of consumption relative to past levels of consumption are important determinants of the utility of current consumption, so we incorporate both aspects into our preference specification.

The way in which we incorporate loss aversion into the individual's preferences is different from the approach taken by Barberis, Huang, and Santos (1999) and Benartzi and Thaler (1995). In these two papers loss aversion is defined with respect to changes in financial wealth and not consumption.

The time dimension of the preferences is modelled with the recursive utility approach of Kreps and Porteus (1978) and Epstein and Zin (1989, 1990). Our economic agent is finitely lived and his preferences depend on the past, so, formally, we work in the framework that is created by Kreps and Porteus (1978) and not in the extended framework that Epstein and Zin (1989) created for the infinitely lived representative agent with history independent preferences. We do use the rank dependent utility preferences as they are discussed in Epstein and Zin (1990, EZ in the sequel).

Let c_{t-1} denote the level of consumption in the previous period and recall the definitions of cash on hand, CH_t, the income state, I_t, and the survival probabilities, $S(t)$. We are now almost ready to define the agents objective function. When individuals maximize expected utility, it is not relevant how they treat the event of dying, as long as the outcome is independent of the level of consumption or cash on hand.[8] However, with probability weighting we have to be more explicit about the way individuals look at their *'life'* after death. We assume that individuals look at the event of dying separately and weight expected future utility with the objective probability that they will survive. Given this assumption the probability of dying does not intervene with the probability weighting process that is used for the computation of expected future utility. With this final assumption, we can now define an agent's total discounted expected future utility at time t, given c_{t-1}, CH_t, and I_t, as follows:

$$V_t(CH_t, c_{t-1}, I_t) = \max_{c_t, \theta_t} \left[U(c_t, c_{t-1}) + \beta S(t) \left(E^{\pi} \{ V_{t+1}(CH_{t+1}, c_t, I_{t+1}) \} \right) \right].$$

The agent's total discounted expected future utility at time t, $V_t(CH_t, c_{t-1}, I_t)$, is defined using $V_{t+1}(CH_{t+1}, c_t, I_{t+1})$. This explains why this is called recursive utility.

The current value of the total discounted expected future utility is obtained

[8]Notice that this rules out bequest motives.

by maximizing current and discounted future utility with respect to the current consumption level, c_t, and the portfolio composition of financial wealth investments, θ_t. These optimal decisions have to satisfy the short sell restrictions on assets, so $\theta_t \in [0,1]$, and the budget constraint defined in (6.1), where CH_t equals $(1 + r + \theta_{t-1}R)A_{t-1} + y_t$.

The final aspect that needs some attention is the modelling of the certainty equivalent functional, E^π. The certainty equivalent we will use is defined by $E^\pi\{x\} = \int x d\left[1 - \pi(1 - F(x))\right]$.[9] $F(x)$ denotes the distribution function and $\pi(.)$ is a transformation function. We follow Prelec (1998) and define $\pi(p)$ as $\exp(-\xi(-\log(p))^\eta)$. This specification permits $E^\pi\{x\}$ to incorporate both expected and non-expected utility models. Some special cases of probability weighting are the types of probability weighting examined by Mehra and Prescott, EZ and Gonzalez and Wu (1999). The model of Mehra and Prescott is the expected utility model and corresponds to the case where $\eta = \xi = 1$, so that $\pi(p) = p$. The models examined by EZ also allow for $\pi(p) \neq p$, but even though the specification we use for $\pi(p)$ directly nests the function p^γ, we can only approximate the model used by EZ. The reason for this is that EZ use a transformation of the cumulative distribution function, $F(x)$, while the more recent literature on probability weighting uses a transformation of the decumulative distribution function, $1 - F(x)$.[10] Gonzalez and Wu (1999) estimate $\pi(p)$ based on experimental data with lottery questions.

Summarizing our model we can say that it consists of the dynamic model used by EZ that allows for probability weighting, while the utility specification is based on BMR in combination with the traditional CRRA utility function. We do not take the pure CPT value function as a preference specification, which is done in BMR. The reason for this is that the empirically estimated value functions do not satisfy the assumptions made by BMR and certainly not the assumptions needed in the multi-period model we use. From preliminary investigations of this specification we concluded that the behavior implied by these preferences is very far away from a meaningful description of the real world.

[9]This cumbersome definition results from the fact that $\mathrm{E}\{x\} = \int x dF(x) = \int (1 - F(x))dx$. The probability transformation was introduced in the last term. This can be rewritten into the more familiar notation as follows: $\int \pi(1 - F(x))dx. = \int x d\left[1 - \pi(1 - F(x))\right]$.

[10]Diecidue and Wakker (1999) call this the *goodnews weighting function* as opposed to the *badnews weighting function* used in EZ.

Solution algorithm

We now have the preferences of the individuals and we know the characteristics of the economy in which the individuals live. Given the budget constraint the agent has to decide how much to save, how much to consume, and how much to invest in the risky asset. In our model the consumption and investment decisions in each period depend only on the level of cash on hand and the income state in that period and on consumption in the previous period. Unfortunately, there are no closed form solutions for the individual's optimal decisions. Thus, we have to solve a problem with two decision variables, current consumption and investment in risky assets, and two state variables, cash on hand and past consumption. We use stochastic dynamic programming techniques (see Deaton (1991)) to compute optimal consumption and investment strategies. This extends the analysis in Hochguertel (1998) and Haliassos and Hassapis (2001).

Most economic applications of stochastic dynamic programming techniques involve discrete state spaces or discrete decisions, see, for example, Rust and Phelan (1997). Moreover, these problems have convex objective functions, making the location of the optimum easier to find. Our preference specification results in a state space with two continuous variables. The approach we take in this chapter to solve the model is to discretize the state space. This is also done in, for example, Hubbard, Skinner, and Zeldes (1995). With this discretization we have to compute the optimal decisions for each grid point in the discretized state space. This is done using a grid search algorithm, which is necessary due to possible nonconvexities of the objective function.[11] Using this approach we obtain the optimal decisions at each grid point in each time period. Details on the solution method are given in Appendix 6.C.

6.4 Optimal behavior

There is little knowledge about optimal savings and investment decisions of individuals in a model in which loss aversion and probability weighting are combined. In this chapter we explore the types of behavior that can be generated with such

[11] Both loss aversion and certain types of decision weighting can result in nonconvexities.

a preference specification. Ideally, one would like to perform a rigorous sensitivity analysis of the model and also gather information about the marginal effects of the various parameters on optimal behavior. Unfortunately, such an extensive analysis of the model is at this moment not feasible, due to the large amount of computer time involved in solving the model.[12] We will explore the possibilities of the preference specification presented in the previous section by looking at optimal behavior for a limited number of different parameter values. The aspects of individual behavior that we are interested in are the optimal portfolio choices, and the consumption and savings decisions. Our main objective is to see whether working with a complex preference specification, like the one we propose, is worth the effort, when one wants to study savings and investment decisions. This will be the case if our preference specification can explain behavior that cannot be explained with other, simpler, preference specifications.

The preference specifications we consider differ mainly with respect to the type of probability weighting and the level of loss aversion. We also vary the shape of the utility function with the parameter w. Only these characteristics are varied, since little is known about their influence on portfolio and savings decisions, while for most of the other parameters this is known. For probability weighting we use the probability weighting function used by EZ, the probability weighting function that was estimated by Gonzalez and Wu (1999, GW in the sequel) and the expected utility (EU) model, where the probabilities are not transformed. For the parameter w, which determines the importance of the reference point, we use three values, which are $w = 0$, $w = 0.2$, and $w = 0.8$. The first value corresponds to the traditional CRRA specification, while the second and third value correspond to models with loss aversion where the functional form is closer to the CRRA value function for the model with $w = 0.2$ than for the model with $w = 0.8$. The model with only the CPT value function, corresponding to $w = 1$, is not considered, since a preliminary analysis showed that very erratic behavior resulted. For LA, the level of loss aversion of the utility function according to our definition above, we use two values, namely LA $= 2.25$, which is the median estimate for the level of loss aversion in Tversky and Kahneman (1992), and LA $= 1.5$, as an intermediate value. These parameter settings are referred to as

[12] Given the increases in computer speed in the past, this problem might be solved in the near future.

LA = 2.25 and LA = 1.5. Loss aversion is not relevant in the model with pure CRRA preferences ($w = 0$) and we refer to this model as the model without loss aversion. The fifteen different models that result from all possible combinations of these parameters are summarized in Appendix 6.B, Table 6.2.

For the remaining parameters in the model we use values that are based on empirical research or values that have been used before in the research on consumption and investment behavior. The level of constant relative risk aversion, ρ, is set to 3, which is the value used by Hubbard, Skinner, and Zeldes (1995). The curvature of the CPT value, α, is set to 0.88, which corresponds to the estimate in Tversky and Kahneman (1992). For the income process we use a set of parameters that is calibrated to the income process estimated by Hubbard, Skinner, and Zeldes (1995) The rate of time preference is set to 2%, as is done in EZ, while Hubbard, Skinner, and Zeldes (1995) use a discount rate of 3%.

When we solve the stochastic dynamic programming problem, we obtain the optimal decisions for an individual in each time period, given the amount of cash on hand and the level of consumption in the previous period. These optimal decisions depend, in general, on the individual's age , income state, and his level of consumption in the previous period. An example of the optimal consumption and asset allocation decisions for an individual aged 40, who consumed US$ 20,000 in the previous period, is presented in Figure 6.2. The preference parameters for this individual are LA = 2.25, $w = 0.2$, and probability weighting according to GW. Notice that the consumption decision is depicted as a function of cash on hand, while the investment decision is depicted as a function of assets, that are to be invested, which equals cash on hand minus optimal consumption. In each graph there are two lines, representing the optimal decisions for the two income states.

The optimal consumption decisions for the two income states overlap due to the discreteness of our solution method. In general, the optimal consumption level is higher for individuals in the high income state, which is what one would expect, since the high income state individual has higher expected lifetime earnings, i.e., a higher human capital.

For the optimal portfolio choices we observe a large difference between the two income states. Furthermore, it might seem counterintuitive that the fraction of financial assets that is invested in the risky asset, decreases with total finan-

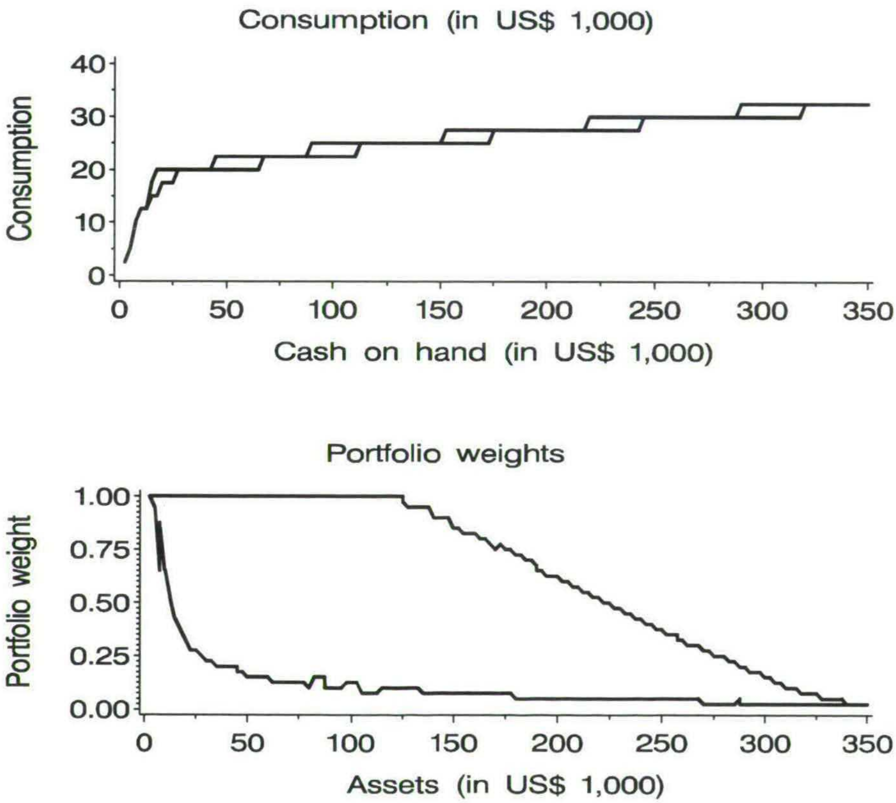

Figure 6.2: Optimal consumption and portfolio decisions (LA=2.25, w = 0.2, GW probability weighting, age=40 and $c_{t-1} = 0.2$).

cial assets. However, we consider the fraction of the amount of *financial assets* invested in the risky asset, while most of the theoretical work derives the optimal fraction of *total wealth* that is invested in the risky asset. Here total wealth is defined as financial assets plus human capital. Early work of Hakansson (1970) and Merton (1971) already shows that CRRA preferences and expected utility imply optimal investments in risky assets that are a constant fraction of total wealth. What we present in Figure 6.2 is the optimal fraction of the total amount of financial assets that is invested in risky assets, as a function of the total amount of financial assets. Let θ_t^* denote the optimal fraction of total wealth to invest in risky assets and let's assume that this fraction is constant, like it is in the case with CRRA preferences and expected utility. Let HC_t denote the individual's human capital at time t, then the total amount of risky assets that an individual would like to hold in period t equals $\theta_t^*(A_t + HC_t)$. The optimal portfolio weight thus equals $\theta_t^*(A_t + HC_t)/A_t$, which is increasing in HC_t/A_t. In the figure we keep the age and income state for the individuals fixed, so the optimal portfolio weight is decreasing in the amount of financial assets. It is increasing with human capital, which results in the difference between the two income states, where the high income state corresponds to the higher portfolio weights.

These optimal consumption and investment decisions are not very informative about what we observe in the real world, if we do not know how cash on hand and consumption evolve over time. To gain insight into the behavior implied by the preference specifications we simulate the income and return processes for a large number of individuals.

In the first period we endow the individuals with an amount of cash on hand equal to US\$ 30,000 and we set the reference level of consumption at US\$ 20,000. The average income at age 25 and average lifetime income are both around US\$ 20,000. The initial reference level thus equals average income, while cash on hand in the first period equals 1.5 time averages income. This includes income in the first period. The income state is randomly assigned to the agents with equal probabilities.

In the first period the optimal decisions only differ due to different realized income states. Depending on the realizations drawn from the income and return distributions in the simulation, the agents will have different situations in the subsequent periods. Since we only know the optimal decisions for the next period at the grid points that are used for the discretization, we take the optimal decision for the agent at the grid point that is closest to his situation, but that at the same time does not violate his budget constraint. We could present optimal individual consumption paths for a number of individuals, but such optimal paths are not very informative about the aggregate behavior that is implied by the model, since these paths depend strongly on the realizations of the stochastic processes. For this reason we present the average behavior for 500 agents, each of them with different realizations of the income and return processes. To make sure that the differences we find are only due to differences between models, we use the same draws from the income and return processes for the simulations for the different models.

The consequences of the different types of probability weighting on consumption, saving, and portfolio decisions are presented in Figure 6.3. The figure presents average optimal behavior for three models that do not have loss aversion. Probability weighting is either done with EU, EZ, or GW. The most important difference between the optimal decisions for the different probability weighting functions is the portfolio choice. The optimal portfolio weights for EU preferences are represented by the solid line in the graph on portfolio weights. It confirms the well known result that, according to EU theory, individuals with reasonable levels of risk aversion invest large parts of their financial wealth in risky assets. The average portfolio weight[13] given to risky assets is close to one during large parts of an individual's life. Only in the ten years before retirement we observe lower optimal risky asset holdings. This is due to the mechanism described above, when we discussed the optimal investment rules. There it was shown that the optimal portfolio weights increase with HC_t/A_t. Since human capital is likely to be decreasing with age and financial assets are at their highest level around the age of 60 or 65, we can expect the portfolio weight to decrease until that age. After retirement the optimal portfolio weight will increase (decrease) when financial assets are reduced at a faster (slower) rate than human capital. It seems that financial assets are reduced faster than human capital, since the optimal portfolio weight increases after the age of 65.

[13]We present the average portfolio weights weighted with the individual's assets. Otherwise the graphs are sensitive to the decisions made by individuals with zero or very small amounts of money to invest.

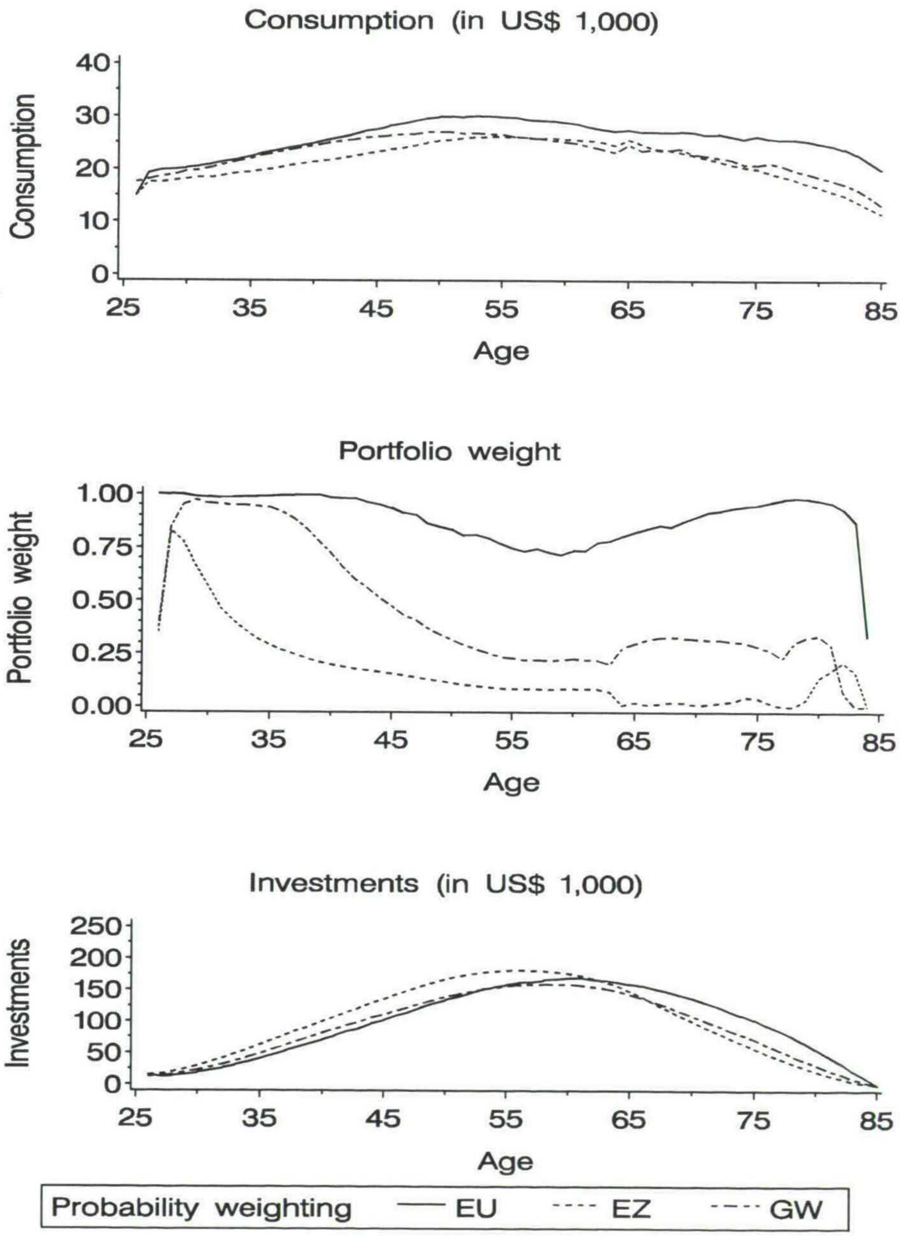

Figure 6.3: The effect of probability weighting on optimal decision making when there is no loss aversion.

The optimal portfolio weights when probability weighting is applied are substantially lower than the optimal portfolio weights implied by EU. The lowest portfolio weights are implied by EZ probability weighting, while the middle line represents the optimal portfolio weights for GW probability weighting. For both types of probability weighting we observe a decline in the optimal portfolio weights with age, which is due to the mechanism described above. At the age of retirement[14] there is a remarkable difference between EZ and GW probability weighting. For GW probability weighting the optimal portfolio weights increase, while for EZ probability weighting the optimal portfolio weights decrease. This difference could be due to a different treatment of the two income states before retirement. With EZ probability weighting the low income state is always overweighted, while with GW probability weighting the current income state is underweighted and the other income state is overweighted, which results in different perceptions of the income process. Moreover, the income and stock return processes are independent, but when we compute the correlation between the outcomes of the income and return processes using the weights that the individuals give to the outcomes, we will find a positive correlation. This 'induced correlation' will be larger for GW probability weighting, since in that case both the very good and the very bad outcomes obtain disproportionately more weight, while this is only the case for the bad outcomes with EZ probability weighting.

The consumption and savings decisions are more difficult to compare, since the different probability weighting functions imply different investment decisions and, therefore, result in different possibilities for total lifetime consumption. Probability weighting results in a small reduction of savings at old age, but, in general, we can say that it does not have a large influence on the consumption and savings decisions, while it has a large impact on the optimal portfolio composition.

The effect of loss aversion on optimal behavior depends strongly on the shape of the utility function. When the utility function is close to the CRRA utility function, $w = 0.2$, loss aversion does not have a large influence on the consumption decision, while it has a negative effect on the optimal investments in risky assets. This effect is much smaller than the effect of probability weighting. The optimal consumption, portfolio choice, and investment decisions for the models with $w =$

[14]Retirement age is the age of 64 in the figures, since income uncertainty has disappeared after the income realization at that age.

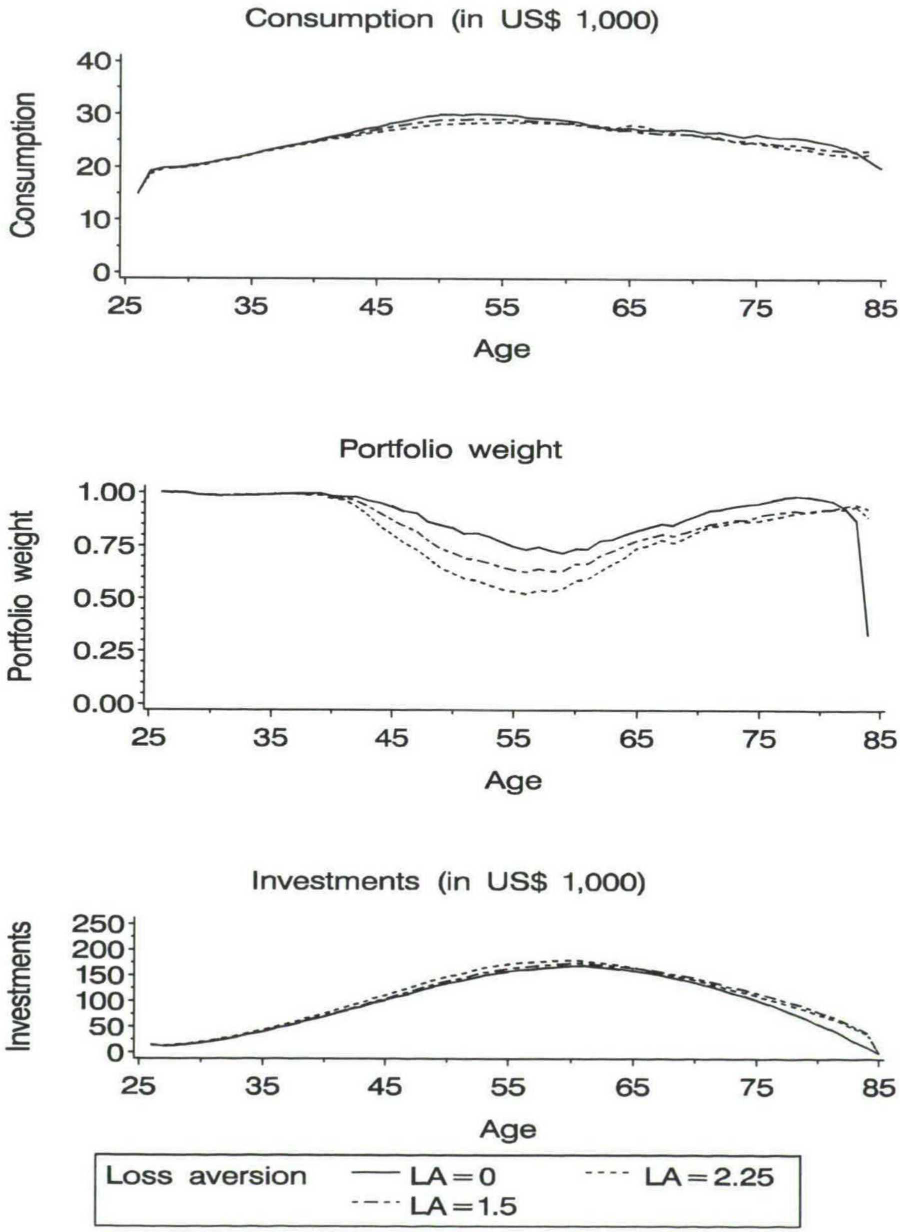

Figure 6.4: The effect of loss aversion with expected utility and $w = 0.2$

0.2 and loss aversion equal to 2.25 and 1.5 and the model without loss aversion, $w = 0$, are presented in Figure 6.4.

The average optimal decisions for the different levels of loss aversion in the model with $w = 0.8$ are presented in Figure 6.5. In this case we have a utility function that is more similar to the CPT value function. The effect of loss aversion on the optimal portfolio weights is larger than the effect with $w = 0.2$, but still not as large as the effect of probability weighting on the asset allocation decision. However, the effect of loss aversion on the consumption and investment decisions is very large. The consumption path is very smooth and individuals build up a large amount of financial assets, enabling them to keep consumption above the reference level, when they receive a low income or a negative return on their investment portfolio.

The amount of financial assets increases until the age of 60, but does not decrease after that age, most likely due to precautionary motives. Individuals hardly dissave after retirement, which is in accordance with observed behavior. Davies (1981) argues that this type of behavior can be obtained when one allows for lifetime uncertainty. With our choice of parameters we have large dissavings for the CRRA and EU preference specification, which contrasts with the result of Davies (1981), but which is similar to the results of Rodepeter and Winter (1998). We obtain low levels of dissaving in our simulations when the effect of the reference point dependent CPT value function is important. Thus, our model is capable of predicting the low levels of dissaving after retirement. It does not predict the fall in the level of consumption after retirement, but, as Banks, Blundell, and Tanner (1998) show, this can be explained by a shift in preferences for consumption, due to changes in household composition and interdependencies between the utility of consumption and leisure. Thus first order risk aversion due to loss aversion with respect to the level of consumption seems to have a large impact on the amount of risk related precautionary savings and provides an explanation for the low levels of dissaving that are observed for the elderly. There is little interaction between the effects of loss aversion and probability weighting, so we do not discuss the models with both loss aversion and probability weighting in detail.

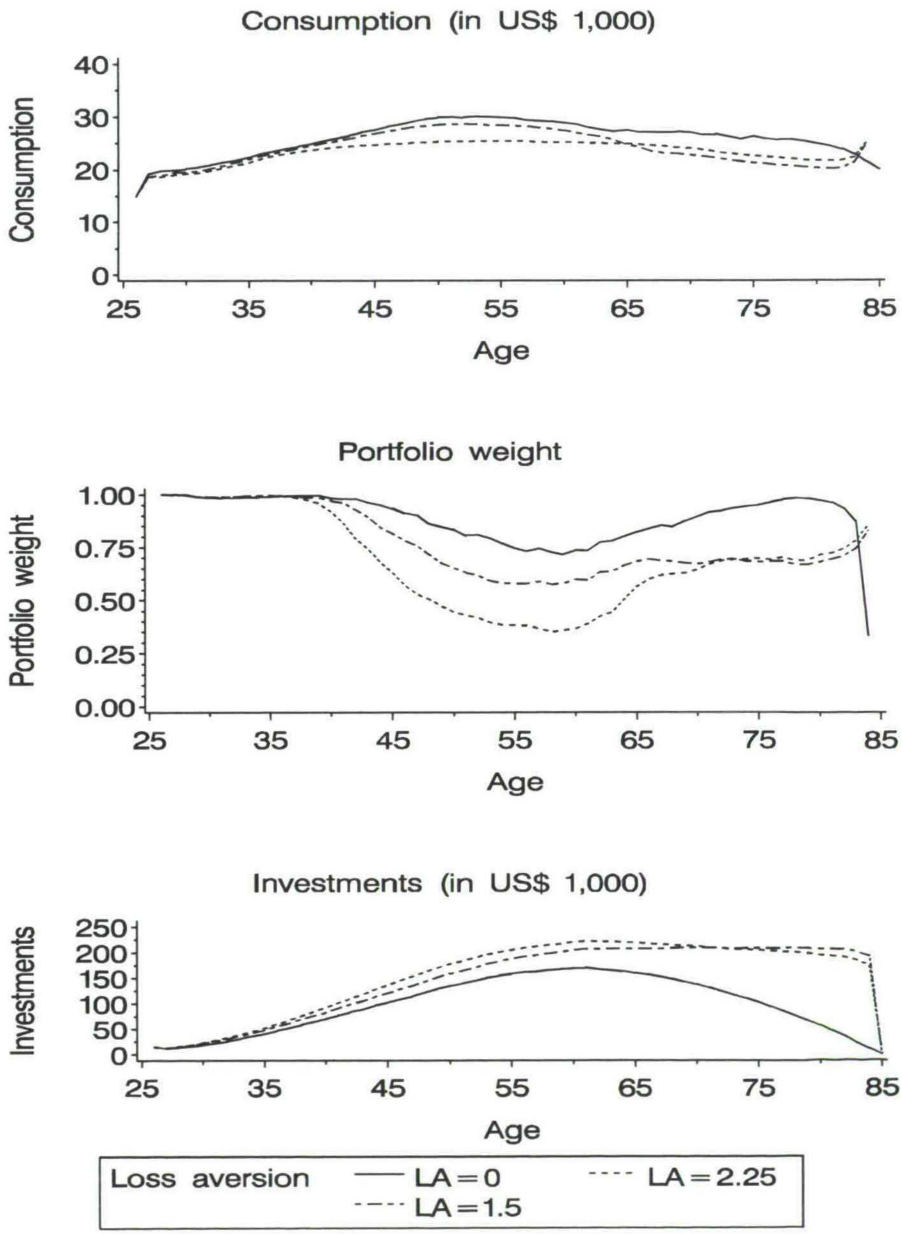

Figure 6.5: The effect of loss aversion with expected utility and $w = 0.8$

6.5 The stock holding puzzle

The previous section presented a general overview of the behavior that is implied by the different preference specifications. We concluded that probability weighting has a large impact on the optimal portfolio composition of an individual. Loss aversion also has an effect on optimal portfolio weights, but this effect is smaller. The remaining question is to what extent the proposed preference specification is capable of solving the stock holding puzzle.

In the recent literature on portfolio composition there are a number of studies concerned with empirical research on portfolio choices over the life cycle. Examples are Bertaut and Haliassos (1997), Heaton and Lucas (1999), and Poterba and Samwick (1997). However, it is difficult to define an empirical measure of the portfolio weight for risky assets that corresponds to the optimal portfolio weights in our model. Bertaut and Haliassos report the portfolio weights of risky assets for the average portfolio of high school graduates, which range from 20% to 60% of directly held financial net worth. Poterba and Samwick use the same data, without conditioning on education level, and report a portfolio weight for the average portfolio of around 20%, while the average portfolio weights are around 6% of total financial assets. From the difference between the reported portfolio weights in these two studies we can conclude that observed portfolio weights depend strongly on the definition of financial wealth that is used. The general conclusion about portfolio weights, however, is that portfolio weights for stocks are rather low, compared to the theoretical predictions of the CRRA model with expected utility. Moreover, only about 20% of the households own equity, either directly or indirectly, as is reported by Poterba and Samwick. This is in accordance with the zero median risky asset holdings reported in Bertaut and Haliassos for households whose head does not have a college degree. For college graduates the reported median risky asset holdings are positive for most age groups.

As is well known from the literature, these observations cannot be reconciled with the CRRA model with expected utility. The average portfolio weights presented in Figures 6.3, 6.4, and 6.5 are weighted with the amount of financial wealth at that age. For this reason the fairest comparison is the comparison with the portfolio weight of the average portfolio. According to Poterba and Samwick this is about 20%, while Bertaut and Haliassos present age and education spe-

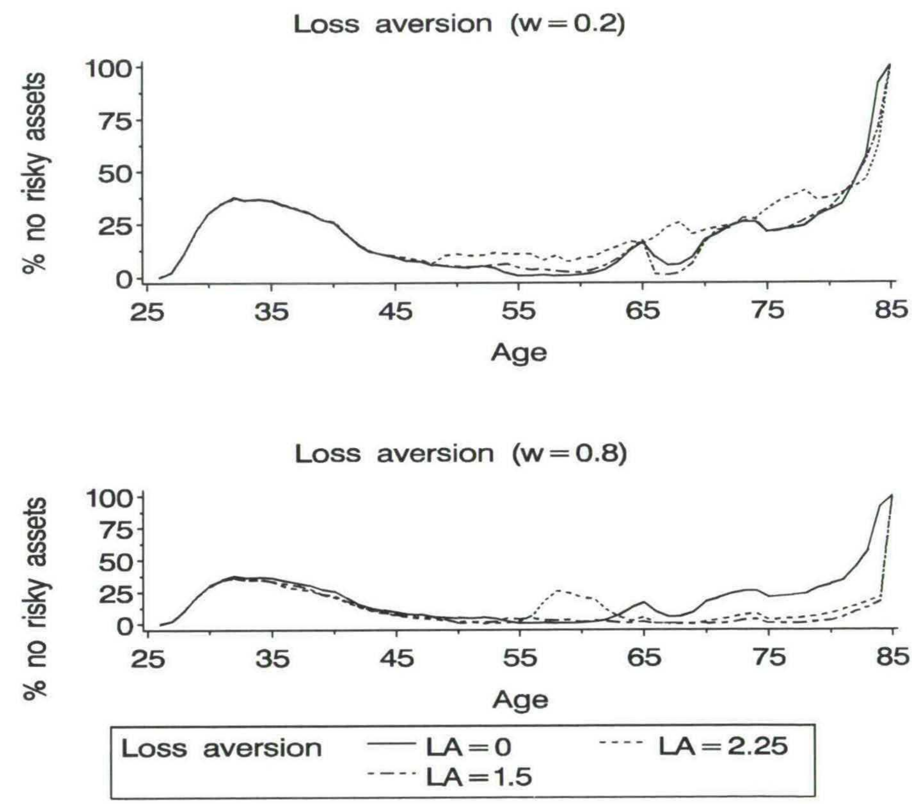

Figure 6.6: The effect of loss aversion on the percentage of individuals that do not own stocks.

cific portfolio weights for risky assets in the average portfolio of about 40%, on average. The models with only loss aversion do not predict such low portfolio weights, but the models with probability weighting result in portfolio weights for the average portfolio that have the same order of magnitude. Probability weighting thus results in a portfolio weight for risky assets in the average portfolio that is of the same order of magnitude as the portfolio weight of the observed average portfolio. This implies that the stock holding puzzle can be solved as far as the average portfolio composition is concerned.

The predicted life cycle profile of the portfolio weights does not coincide very

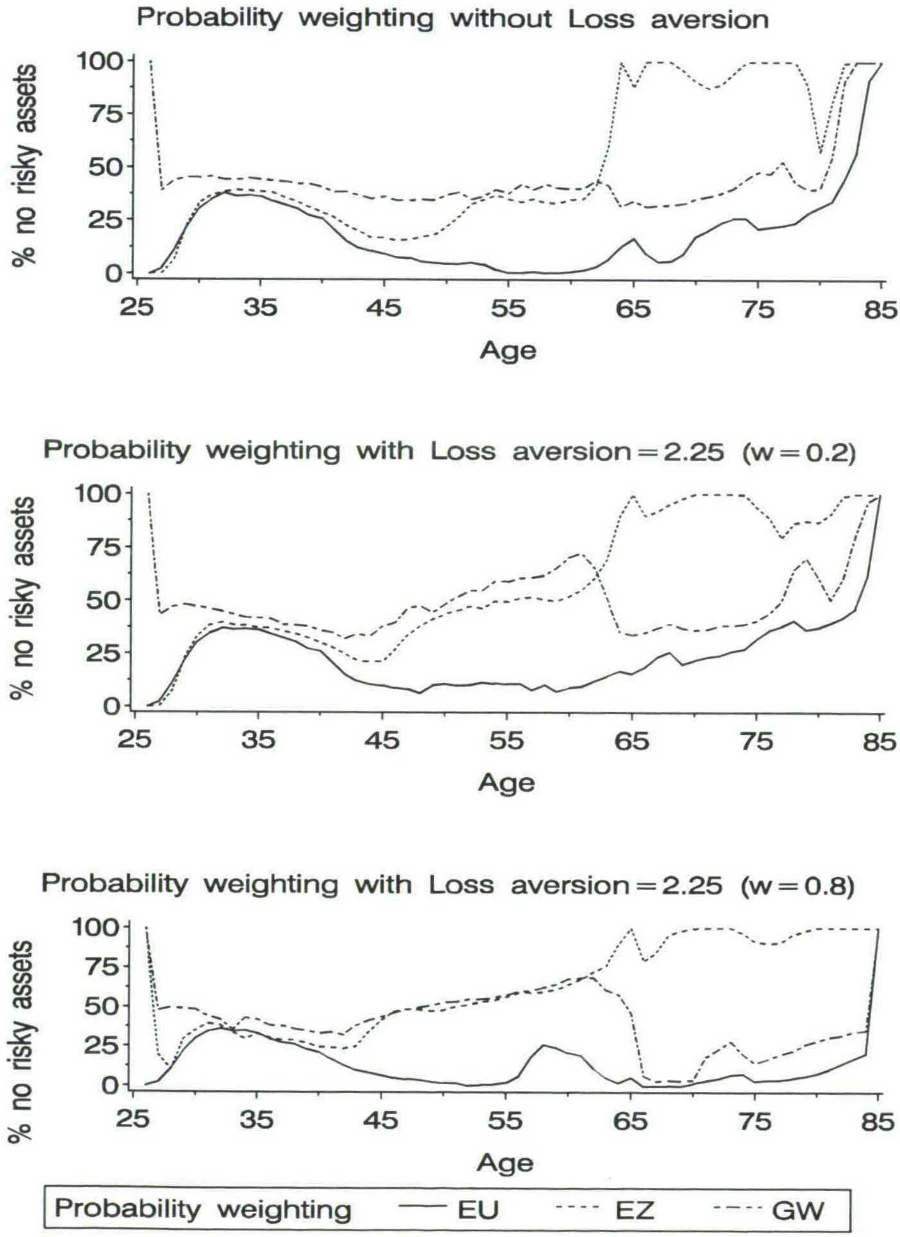

Figure 6.7: The effect of probability weighting on the percentage of individuals that do not own stocks.

well with the observed pattern that is presented in Bertaut and Haliassos. The model predicts high investments in the risky asset for young individuals, while this is not observed in the data. An explanation for this might be the purchases of durables, especially housing, early in the life cycle This is not incorporated in our model, but plays a very important role for young people. If young individuals plan to buy a house, they are more likely to encounter binding credit constraints, which shortens their investment horizon along the lines of Carroll and Kimball (1999). With a shorter horizon individuals might be less likely to invest in the risky asset.

The stock holding puzzle is also based on the low number of households that own risky assets. The reported median stock holdings for high school graduates in Bertaut and Haliassos is zero for all age groups and Poterba and Samwick report that approximately 20% of all households own stocks. In Figures 6.6 and 6.7 we present for different models the life cycle profile of the percentage of households that do not own stocks. We define a household as such, if the household's optimal portfolio weight is less than 5%, or if the optimal amount of money to invest in the risky asset is below US$ 5,000.[15] In reality there are fixed costs for investing in the stock market and such individuals are not likely to incur these costs, so they will not own risky assets.

In Figure 6.6 we present the percentage of households that do not own stocks for models with loss aversion, but without probability weighting. The effect of loss aversion is only small and for all models the percentage of households that do not own stocks is far below the observed 80%. The high number of households that do not own stocks early in life is due to the low levels of savings in that period of the life cycle.

Once probability weighting is introduced in the preference specification, the results change considerably, as is shown in Figure 6.7. In this figure we present the effect of the three types of probability weighting on the percentage of households that do not own stocks for the preference specifications that differ with respect to the shape of the utility function. In the top panel we present the models without loss aversion. From this graph we see that the percentage of households that do not own risky assets is substantially higher for the models with probability

[15] Of course, this definition is based on arbitrary numbers, but the results are not very sensitive to small changes in these numbers.

weighting, when they are compared with the predictions of the expected utility model, which is represented by the solid line in the graphs.

After retirement there is a large difference between EZ and GW probability weighting. EZ probability weighting implies that almost every household has only the riskless asset in its investment portfolio, while for GW probability weighting the percentage of households without risky assets drops initially and then slowly increases with age. This large change in behavior is caused by the fact that there is no income or expenditure risk left after retirement, only the lifetime uncertainty remains. This is not likely to result in the large difference between the two models, since it is modelled independently from the outcome distribution and results in a time varying discount rate. The difference between the two types of probability weighting might disappear when we introduce other risks, like the uncertainty in medical expenses, as it is done in Hubbard, Skinner, and Zeldes (1995).

The middle and bottom panel of Figure 6.7 deal with the models with loss aversion. During working life the percentage of households that do not own stocks increases, due to the introduction of loss aversion. Up to the age of retirement, the two different types of probability weighting result in similar patterns for the percentage of the households that do not own stocks. The predictions are more in line with the stylized facts than the predictions of the expected utility model, and when reasonable transaction and information costs are imposed, the model seems capable of predicting the level of stock holding incidence for middle aged households. For younger people the model overpredicts the holding of risky assets. An motivation for this, based on the purchase of durables early in life, is already given when we described the optimal portfolio weights in the previous section. The difference between the two types of probability weighting after retirement is larger when loss aversion is introduced, but this difference will be reduced when there is also uncertainty about income or expenditures in the retirement period.

New types of preference specifications, other than the CRRA preferences with expected utility, can solve a large part of the stock holding puzzle. Especially preferences with probability weighting are very helpful, since the introduction of probability weighting into the preference specification results in a substantial reduction of the optimal holdings of risky assets. The explicit introduction of transaction costs in our model with the broad class of preference specifications will make the solution of the model infeasible. The combination of probability weighting and transaction costs, without loss aversion, might be a good step to continue this line of research and to solve the stock holding puzzle.

6.6 Discussion

In this chapter we try to find preference specifications that solve the stock holding puzzle and, therefore, are possible candidates for the solution of the equity premium puzzle. Starting point for the preference specifications we consider is the concept of first order risk aversion, as it is defined by Segal and Spivak (1990). We described a class of preference specifications that display first order risk aversion. There are two basic ideas behind the preference specifications, which are loss aversion and probability weighting. Both concepts are well known in the economic and psychological literature on decision making under risk and uncertainty. In this field there is one very frequently used theory, which combines the two concepts. This theory is Cumulative Prospect Theory (Tversky and Kahneman (1992)) and our preference specifications are based on it.

We analyze the consequences of loss aversion and probability weighting using the optimal consumption, investment, and savings decisions of individuals with such preferences. The individuals face three types of uncertainty that are important for their decisions, which are the uncertainty due to the asset returns, the income distribution, and the uncertain lifetime. The optimal decisions are derived with stochastic dynamic programming techniques. This results in the consumption and investment strategies in each period, given the past. Using the optimal decisions we simulate the income and return processes to find the optimal consumption, investment, and savings paths for a large number of individuals. We analyze the differences in optimal behavior between the preference specifications based on these average consumption, savings, and investment paths.

The introduction of probability weighting in the model, either by using the probability function used by Epstein and Zin (1990) or by using the probability weighting function estimated by Gonzalez and Wu (1999), results in substantially lower investments in the risky asset. Probability weighting might thus be a good candidate for the solution of the stock holding and equity premium puzzles. Not only the average portfolio weight for risky assets is reduced, but also the percentage of individuals that hold only very small amounts of stocks is increased substantially, which makes the stock holding puzzle less puzzling. Probability weighting has a small impact on the consumption and savings decisions.

Loss aversion does not have a large impact on the portfolio composition, but it can influence the savings decisions substantially. This is the case when the utility function is close to the value function used in CPT. In this situation individuals save more to create a large buffer to make sure that they do not have to consume below their reference point. With the preference specifications without loss aversion the individuals use this buffer to increase their consumption after retirement, but this is not the case when loss aversion is important. In this case the individuals hardly dissave after retirement. Low dissavings of the elderly is a phenomenon that is observed in the real world, but that has been difficult to explain with the traditional economic models. Our results indicate that preferences with loss aversion are able to explain this phenomenon.

Our results indicate that preferences with first order risk aversion can be very useful in the analysis of economic decision making. Both loss aversion and probability weighting have a large impact on the optimal decisions that an individual will make. However, their influences are qualitatively different. Loss aversion influences the consumption and savings decisions, while probability weighting has a large impact on the optimal asset allocation. Thus, for most economic problems the extensions to the CRRA expected utility model, that we introduced, will have a substantial impact on the solution.

In this chapter we present a model for economic decision making. Our model is different from the expected utility model in the sense that the expected utility model is used both descriptive and normative or prescriptive, while our model is only meant to be descriptive, see Schoemaker (1982). Our model describes how individuals might make their decisions, it certainly does not describe how we think individuals should make their decisions. With respect to loss aversion there is no difference when it is approached from a descriptive or a normative viewpoint. If individual preferences display loss aversion, this will be the case and there is no reason to change this. However, for probability weighting there is, in our opinion, a difference between the descriptive and the normative point of view. Probability weighting might be very important in descriptive models of economic decision making, but it should not be present in a normative model.

6.A Specification of the economy

Survival probabilities

Table 6.1: Conditional probabilities of not surviving age i.

Conditional probabilities of not surviving age i, given surviving up to age $i-1$.					
Age	Probability	Age	Probability	Age	Probability
25	0.00064	45	0.00242	65	0.01332
26	0.00065	46	0.00266	66	0.01455
27	0.00067	47	0.00292	67	0.01590
28	0.00069	48	0.00320	68	0.01730
29	0.00070	49	0.00349	69	0.01874
30	0.00072	50	0.00380	70	0.02028
31	0.00075	51	0.00413	71	0.02203
32	0.00078	52	0.00450	72	0.02404
33	0.00082	53	0.00490	73	0.02623
34	0.00086	54	0.00533	74	0.02863
35	0.00091	55	0.00581	75	0.03128
36	0.00098	56	0.00632	76	0.03432
37	0.00105	57	0.00689	77	0.03778
38	0.00115	58	0.00749	78	0.04166
39	0.00128	59	0.00811	79	0.04597
40	0.00144	60	0.00878	80	0.05078
41	0.00161	61	0.00952	81	0.05615
42	0.00180	62	0.01033	82	0.06214
43	0.00200	63	0.01124	83	0.06885
44	0.00221	64	0.01223	84	1.00000

Source: Faber (1982), taken from Hubbard, Skinner, and Zeldes (1993).

Income process specification

The income process we use is based on the empirical results in Hubbard, Skinner, and Zeldes (1995, HSZ). They estimate an income process for three different education groups, based on a two step estimation strategy. The data they use come from the PSID from 1982 until 1986. First, they estimate the mean income profile as a function of age. Second, they use a regression model for log(income) to estimate the dynamic effects of the income process. Detailed results are presented in Hubbard, Skinner, and Zeldes (1993). We will use their results for high school graduates as a benchmark.

HSZ model mean income at a given age with a third order polynomial in age and estimate the parameters in this polynomial with OLS. To get a grip on the dynamic aspects of the income process HSZ specify a regression model for log(earnings) as follows:

$$y_{it} = Z'_{it}\beta + u_{it} + v_{it}$$

The term u_{it} is then specified as:

$$u_{it} = \rho u_{it-1} + \varepsilon_{it}$$

Here y_{it} denotes log(income) of household i in period t and $Z'_{it}\beta$ is a polynomial in age and time dummies. Deviations from the average are modelled with two terms: u_{it} and v_{it}. Both ε_{it} and v_{it} have zero means and variances of σ_e^2 and σ_v^2, respectively. The term u_{it} is the permanent component of the shocks in the income process, which has some persistence across time, measured by the correlation coefficient, ρ. The term v_{it} denotes the transitory part of the income shocks. The parameter estimates HSZ report for the error components are:

σ_ε^2	σ_v^2	ρ
0.025	0.021	0.946

We approximate this income process with a mixture of a discrete and a continuous process. We use two discrete stochastic income states, I_t, that represent the state of permanent income for the individual. This income state is modelled as a first order Markov process to capture the persistence of the permanent income shocks across time. Conditional on the income state we model the transitory shocks by a continuous distribution.

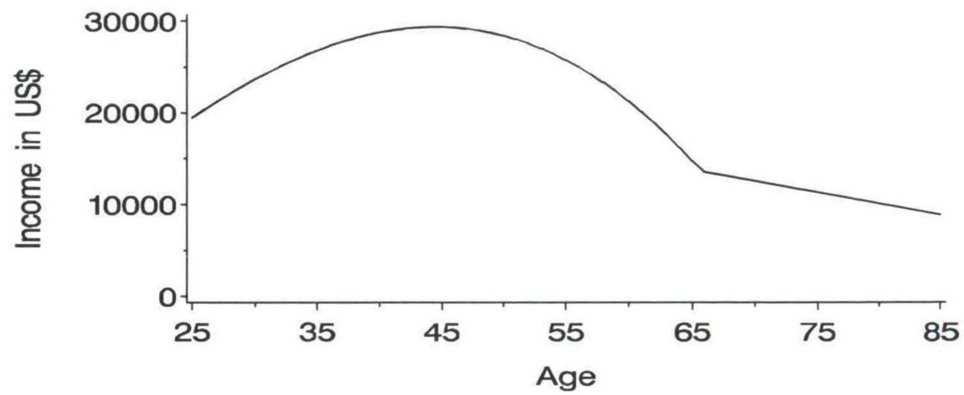

Figure 6.8: Age profile for average income

To make this more precise we start with defining the life cycle income profile. Let μ_{age} denote the age dependent mean income, then μ_{age} follows the age polynomial that is estimated by HSZ for high school graduates. This income profile is presented in Figure 6.8. If we denote the two income states at a given age with I_{age}^L and I_{age}^H, where L and H denote the low and high income state, respectively, we can define the age and income state dependent mean incomes, μ_{age,I_{age}^L} and μ_{age,I_{age}^H}, which satisfy $\mu_{age,I_{age}^L} < \mu_{age} < \mu_{age,I_{age}^H}$. The values of these income state dependent means are proportional to μ_{age} and chosen such that average income equals μ_{age} and the unconditional variance of the permanent income process equals the (unconditional) variance of the income process as it is estimated by HSZ.

For computational reasons we assume that income conditional on age and the income state follows a normal distribution, so:

$$\text{income}|\text{age}, I_{age} \sim N(\mu_{age,I_{age}}, (\sigma_{age} \cdot \mu_{age,I_{age}})^2),$$

where $I_{age} \in \{I_{age}^H, I_{age}^L\}$. The standard deviation of the conditional income distribution is thus proportional to the conditional mean of the distribution. During the working life, the coefficient of variation[16] of the conditional income distribution, σ_{age}, is set to 0.15 for all ages. This approximates the variance of the

[16] The coefficient of variation is defined as the ratio of the standard deviation to the mean. We denote this with the parameter σ, because it coincides with the variance of the residuals in the log(income) model.

transitory shocks, $\sigma_v^2 = 0.021$, in the estimated log income process that was estimated by HSZ. When the individuals are older than 64, they are retired and they receive an age dependent income without uncertainty.

To capture the persistence of the permanent income shocks across time we need persistence in the income states. The level of persistence, that is estimated by HSZ, is obtained by setting the transition probabilities for the income states as follows: the probability that the income state changes from high to low or the other way round equals 2.7%. The probability that the income state does not change is thus 97.3%. This high value is due to the large persistence in the permanent income shocks.

Summarizing the proposed specification for the income process, we model the process for changes in permanent income using two discrete income states with different conditional means. The transitory shocks are captured by the normal distribution of income given the income state. When retired the income uncertainty disappears.

HSZ approximate the permanent shocks in the income process with a first order Markov process with nine discrete income states, but they ignore the transitory shocks. The income in each of these nine income states at a certain age depends on mean income in a similar way as we model it.

6.B Preference specifications

Table 6.2: Different combinations of the parameters for the model specifications that are considered.

model	Probability weighting	Loss aversion	w
1	EU	x	0
2	EZ	x	0
3	GW	x	0
4	EU	2.25	0.2
5	EZ	2.25	0.2
6	GW	2.25	0.2
7	EU	2.25	0.8
8	EZ	2.25	0.8
9	GW	2.25	0.8
10	EU	1.5	0.2
11	EZ	1.5	0.2
12	GW	1.5	0.2
13	EU	1.5	0.8
14	EZ	1.5	0.8
15	GW	1.5	0.8

Note: EU = expected utility, EZ = probability weighting according to Epstein and Zin (1990), GW = probability weighting according to Gonzalez and Wu (1999)

6.C The dynamic optimization algorithm

We assume that individuals maximize total lifetime utility in the first period given the budget constraints in each period. The maximization problem in each period, except for the final period is the following:

$$V_t(CH_t, c_{t-1}, I_t) = \max_{c_t, \theta_t} \left[U(c_t, c_{t-1}) + \beta \left(E^{\pi}\{V_{t+1}(CH_{t+1}, c_t, I_{t+1})\} \right) \right], \qquad (6.2)$$

given the budget constraints in each period.

This complicated problem can be solved using stochastic dynamic programming techniques. We start with the determination of the optimal decisions in the last period. The optimal decisions in the last period are not too difficult to find, since any assets that are left after this period do not yield extra utility, while consuming it in the last period does yield extra utility. Since total assets have to be non-negative, it is optimal to use all available assets in the final period for consumption. The investment decision in this period becomes immaterial, since there are no assets left to invest.

We are thus able to determine the value of having an amount of cash on hand, CH_T, in the final period, period T, given consumption in period $T-1$, c_{T-1}. With this information we can determine the optimal investment and consumption decisions in the one but last period, given the amount of cash on hand in that period, the consumption level in the period before and the income state. The objective function, however, is not globally concave, so using a local search algorithm for finding the optimal consumption and investment decision does not guarantee us that we find the globally optimal decisions. We use a grid search algorithm to find the optimal consumption and investment levels in each period. Thus, the model is solved completely numerically. The discretization of the relevant variables is done as follows: Cash on hand is assumed to take on the $N_{CH}+1$ values from $\frac{4}{N_{CH}}, \frac{8}{N_{CH}}, \ldots, \frac{4(N_{CH}-1)}{N_{CH}}, 4, \frac{4(N_{CH}+1)}{N_{CH}}$. This set of grid points is denoted as $\mathcal{CH}$. The same type of discretization is used for the portfolio weight with $N_\theta + 1$ values, ranging from 0 to 1. For the level of consumption we decided to have the same distance between two grid points as for the cash on hand grid. We used a smaller grid range for consumption, ranging from $\frac{4}{N_{CH}}$ to 1. Although there is no a priori justification of this smaller grid, we can still scale the problem in such a way that the range over which the grid search is performed, is large enough. A grid that is not large enough can result in large truncation errors and a bad approximation to the optimal decisions of the problem. Simple checks to see whether the grid range is large enough are how frequently cash on hand is higher than the maximum of the grid and how often we find optimal consumption levels that are close to the maximum consumption level imposed by the grid. The realization of income in each period is incorporated in the amount of cash on hand, leaving us with the N_I discrete income states in the set of income states,

$\mathcal{I}$, as the relevant state space parameter, so we do not need a discretization for the income process.

First, we describe how an approximation of the value function in period t is calculated given the level of consumption in period t and in period $t-1$, the level of cash on hand in period t, CH_t, the income state in period t, I_t, the portfolio weight given to the risky asset in period t, θ_t, and the value function[17] in period $t+1$ for each point in the grid defined by the grids for consumption and cash on hand in period $t+1$.

The first part of the value function, as it is defined in equation (6.2), is easy to determine with the information we have. It is the utility of consuming c_t given that consumption in the previous period was c_{t-1}, which both are given. The difficult part is in the computation of the second part of the right hand side of (6.2). We know the value of $V_{t+1}(CH_{t+1}, c_t, I_{t+1})$ at the grid points of CH_{t+1} and c_t. Using CH_t and θ_t we can derive the distribution of the asset level in period $t+1$, which is the distribution of $(1+r+\theta_t R)(CH_t - c_t)$. We also know I_t and the transition probabilities between income states, so we can compute the distribution of the next period's income state, I_{t+1}. Conditional upon the next period's income state, I_{t+1}, we know the distribution of next period's income, y_{t+1}, so we can compute the distribution of CH_{t+1} conditional on I_{t+1}, since $CH_{t+1} = (1+r+\theta_t R)(CH_t - c_t) + y_{t+1}$. This enables us to approximate

$$E_t[V_{t+1}(CH_{t+1}, c_t, I_{t+1})] =$$
$$\Sigma_{i\in\mathcal{I}} P(I_{t+1} = i|I_t) \int_0^\infty V_{t+1}(CH_{t+1}, c_t, i) f(CH_{t+1}|I_{t+1} = i) dCH_{t+1}$$

with

$$\Sigma_{i\in\mathcal{I}} P(I_{t+1} = i|I_t) \Sigma_{CH\in\mathcal{CH}} V_{t+1}(CH, c_t, i) P(CH_{t+1} = CH|I_{t+1} = i),$$

where $f(CH_{t+1}|I_{t+1} = i)$ denotes the probability density function for next period's cash on hand[18] given next period's income state. $P(CH_{t+1} = CH|I_{t+1} = i)$

[17] Exept for the last period we only have approximations to the value function. This is not made explicit in the remaining part of the text.

[18] CH_{t+1} follows a normal distribution under the assumptions made in this paper. To save some computer time the program makes use of a standardized normal density over the interval $(-7.5; 7.5)$. The remaining probability mass is attributed in two equal amounts to the points -7.5 and 7.5.

denotes the probability mass attributed to grid point CH, based on a discretization[19] of $f(CH_{t+1}|I_{t+1} = i)$.

However, we are also interested in models with probability weighting, like the model used by EZ. To solve such models, we need a more complicated structure. With probability weighting we need the distribution function of the value in the next period, V_{t+1}. We can construct an approximation of the distribution function of V_{t+1} from the underlying distribution of the income state and the level of cash on hand. To do this we create a ranking of $V_{t+1}(CH, c_t, i)$ as a function of CH and i.[20] If there is a tie we give the low income state the lowest place in the ordering of $V_{t+1}(CH, c_t, i)$. If we denote these ranks, obtained from ranking V_{t+1}, by $\text{Rank}(CH, i)$, and with $I\{.\}$ the usual indicator function, then we can define the decision weight, $\text{DW}(CH_{t+1}, I_{t+1}|I_t)$, given to $V_{t+1}(CH_{t+1}, c_t, I_{t+1})$ as follows:

$$\begin{aligned}
\text{DW}(CH_{t+1}, I_{t+1}|I_t) &= \\
\pi(\Sigma_{i\in\mathcal{I}}\Sigma_{CH\in\mathcal{CH}}P(I_{t+1} &= i|I_t)P(CH_{t+1} = CH|I_{t+1} = i) \\
\cdot I\{\text{Rank}(CH, i) &\geq \text{Rank}(CH_{t+1}, I_{t+1})\}) \\
-\pi(\Sigma_{i\in\mathcal{I}}\Sigma_{CH\in\mathcal{CH}}P(I_{t+1} &= i|I_t)P(CH_{t+1} = CH|I_{t+1} = i) \\
\cdot I\{\text{Rank}(CH, i) &> \text{Rank}(CH_{t+1}, I_{t+1})\}).
\end{aligned}$$

The rank of the value function is independent of the income state in the previous period, but the decision weights depend on I_t because the probabilities for the level of cash on hand and the income state, $P(I_{t+1} = i|I_t)P(CH_{t+1} = CH|I_{t+1} = i)$, depend on it.

$E_t^\pi[V_{t+1}(CH_{t+1}, c_t, I_{t+1})]$ can now be approximated with a simple summation:

$$\Sigma_{i\in\mathcal{I}}\Sigma_{CH\in\mathcal{CH}}V_{t+1}(CH, c_t, i)DW(CH, i|I_t).$$

In the situation where $\pi(p) = p$, so the probabilities are not transformed, we have

$$DW(CH, i|I_t) = P(I_{t+1} = i|I_t)P(CH_{t+1} = CH|I_{t+1} = i).$$

[19] The probability mass attributed to a point CH is the total probability attributed by $f(CH_{t+1}|I_{t+1} = i)$ to the interval of length $\frac{1}{N_{CH}}$ with the point CH as its midpoint. For the highest (lowest) value of CH this interval is extended upward (downward) to cover the whole support of the distribution.

[20] This ranking also depends on c_t, so the decision weights also depend on it, but this is not made explicit for notational convenience.

The optimal consumption and investment levels are now found by performing a grid search over the grid that is created by combining all possible values of the grids for consumption and the portfolio weight and computing the value function in each of these points as is described above. The optimal decisions are the decisions that result in the highest objective value. This is a two dimensional optimization over a grid of $\frac{1}{4}N_{CH} \times (N_\theta + 1)$ points. This grid search is performed for each possible combination of the level of cash on hand, consumption in the previous period, and the income state, where the level of cash on hand and the consumption level are discretized as described above. Thus the optimization is performed a total of $\frac{1}{4}N_{CH} \times (N_{CH} + 1) \times N_I$ times.

Chapter 7

Discussion

In this chapter we deal with some of the open questions that remain, when one wants to use subjective information in empirical economics. This chapter does not present an overview of the results of this thesis, but describes ways in which the results can be used. The overview of this thesis can be found in the introduction.

The analysis in Chapter 2 was based on reduced form models of economic decision making. However, in most of the economic models, the rate of time preference and the level of risk aversion enter the individual's decision making process in a particular way, so direct measures of time preference or risk aversion can be even more useful in structural models of economic decision making. Most of the structural models that are currently used in empirical economics can easily be modified to include direct information about individual preferences. Subjective information can also be used in the model presented in Chapter 6, but the computational burden of solving such a model makes it, at least with the current state of computer technology, not suitable for empirical applications.

In this thesis three chapters deal with the analysis and interpretation of answers to questions that are subjective in nature. The subjects of these three chapters are the subjective income distribution, the rate of time preference, and the level risk aversion. However, in these chapters there is no explicit discussion about whether the measurement of these quantities can be improved and how these measures can be used in empirical applications. Part of this chapter will be concerned with this question.

Chapter 3 deals with the analysis of questions related to the respondent's subjective future income distribution. The questions that are used in the CentER Savings Survey to measure the subjective income distribution seem appropriate. Some improvements can and have already been made. One way to improve the measurement of the subjective income distribution is to ask the respondents for a number of possible changes that can happen and the probabilities with which they think these events occur. After these questions the respondents can then be guided through a sequence of questions dealing with the subjective income distribution, conditional on the events that can occur. It could be interesting to ask for the subjective income distribution, conditional on events like keeping the same job, becoming unemployed, disabled, or working part time. The combination of the subjective probabilities for the events and the conditional subjective income distributions can result in a more detailed description of the respondent's subjective income distribution.

Chapter 3 presented a descriptive analysis of the subjective income distribution of the respondents and of a measure of income uncertainty that is derived from the subjective income distribution. The chapter does not deal with the question how the information in the subjective income distribution can be used. One could use the subjective income distribution in modelling savings decisions in a structural model. Suppose one is interested in estimating an empirical model based on the Euler equation, then it is usually assumed that, on average, today's marginal utility equals the expected discounted marginal utility in the next period. The average here is computed with respect to the sample distribution of income realizations, possibly conditional on certain characteristics. This procedure is only justified if the empirical income distribution is equal to the respondent's subjective distribution. A better procedure would be to use the subjective income distribution to weight the possible outcomes in the next period, instead of using the sample weights.

The two procedures mentioned above might suffer from two other problems. The first one is a completely different problem and based on the findings, presented in Chapter 4, that empirical models that use decision weights seem to perform better in describing individual behavior than models using objective probabilities. If one wants to apply probability weighting in the empirical model, one should use weights for the observations in the sample that correspond to a transformed empirical or subjective income distribution for each individual. Evidence and a theoretical treatment about the difference between decision weights and subjective probabilities, like the subjective income distribution, is presented in Tversky and Wakker (1998). The second problem is the possible presence of macroeconomic shocks, since, in their presence, income realizations of the following period do not provide information about the income uncertainty due to macroeconomic shocks. If this is taken seriously, the subjective income distribution is more difficult to use in the way described above, since it incorporates the perceived uncertainty due to the macroeconomic shocks, while the observations apply to only one realization. One could use the (transformed) subjective income distribution directly and make assumptions about the utility of the states that did not realize, or obtain information about income realizations in a large number of periods.

Finally, it might be the case (some people even think this is very likely) that individuals do not have a single subjective probability for each event, but some set of possible probabilities. This phenomenon is called ambiguity, see Fox and Tversky (1995). There are theories that deal with decision making under ambiguity, but such theories are rather difficult to use in empirical applications on economic decision making. At least, it seems impossible to infer such a range of probabilities directly. Asking respondents about the probabilities of certain events is possible, although one has to be careful. Asking for the highest and lowest possible probability of an event results most likely in confusion for the respondents and not in information for the researcher. In principle, it is possible to construct ranges of probabilities by asking questions about lotteries where the outcomes depend on the event under consideration, but the number of questions needed to obtain precise bounds on a large number of events may become enormous. Although it might be the only way to obtain this type of information, it may be very cumbersome and time consuming.

The best way of using the respondent's subjective income distribution might very well be a reduced form approach, where the subjective income distribution is summarized with, for example, the median and the interquartile range. Such measures are not very sensitive to probability weighting and they include the perceived uncertainty due to macroeconomic shocks, which is otherwise very difficult to deal with.

In Chapter 4 we estimated an empirical model based on Cumulative Prospect

Theory (Tversky and Kahneman (1992)), using three questions on lotteries. The estimation results show that in this model risk aversion cannot be measured with a single number. Both the value function and the decision weighting function influence an individual's attitude to risk. The amount of systematic variation in the decision weighting function, however, turned out to be rather small. This result is not necessarily in contradiction with the results of Gonzalez and Wu (1999), who find that there is substantial variation in the decision weighting function. We considered only the amount of systematic variation that we could control for with a set of observed characteristics and this turned out to be small. Thus, in reduced form empirical applications, it might suffice to take into account the interpersonal variation in the shape of the value function. In structural models of economic decision making under risk or uncertainty, it still might be important to take into account the interpersonal variation in the decision weighting function, but this has to be taken care of with some sort of unobserved heterogeneity.

Even though we found little systematic variation in the probability weighting function, this information might still be useful. For many economic decisions the size of the distortion between objective probabilities and decision weights might be far more important than the level of risk aversion that is measured by the curvature of the value function. For many individuals that buy lottery tickets, the main reason why they buy lottery tickets, might be the mere fact that they can win very high prizes. These individuals might be hardly interested in the exact probability of winning this prize. A less trivial example is the decision to buy insurance, which depends strongly on the decision weight given to the event one wants to buy insurance against.

From our analysis we learned much about the differences between the decision making processes of individuals. With an extended questionnaire we can even solve the identification problems, that occurred when we estimated our empirical model in Chapter 4. Moreover, we can do research on the level of loss aversion, the decision weighting function for negative outcomes, etc. In general, there is still much more to be learned about the variation across individuals in decision making under risk and uncertainty.

In Chapter 5 we analyzed questions about intertemporal choices. We used information from a set of sixteen questions related to delaying or speeding up payments or receipts in time. When one wants to use such information in an empirical model, one has to realize that it is almost impossible to identify the level of the rate of time preference. We can think of two ways to do this, but both of them are not very attractive. The first way is simple from the point of view of the researcher, but the respondents have to answer questions with at least three outcomes at different points in time. The second way is to obtain information about the value function. However, there might be a difference between the value function for certain and uncertain outcomes. The difference in the level of loss aversion that is observed in Chapters 4 and 5 indicates that there certainly is a difference in loss aversion in risky and riskless choices. This does not mean that the curvature of the value function has to be different in the two situations.

However, one can easily think of situations where the level of the rate of time preference is not needed, since it is sufficient to know how subjective discount rates differ across individuals. An example of such a situation is the estimation of the returns to schooling, when one wants to correct for the variation in the individual rates of time preferences. The information about the variation across individuals can be taken directly from the estimates we have presented.

Based on the model we use in Chapter 5, it is possible to create an individual specific measure of impatience that is not sensitive to the variation in the level of loss aversion. If the questions are symmetric in terms of speeding up and delaying gains and losses, then a simple measure of impatience can be obtained by multiplying all the observed implied discount factors. In this measure the level of loss aversion does not play a role anymore. Unfortunately, this is not possible with the questions in the CSS, since only non-negative observed discount rates are allowed for, so the observed discount factors are censored.[1]

Before we discuss the results in Chapter 6, there is one thing that has to be mentioned about the model that is presented there. This model is meant to be a descriptive model and certainly not a normative or prescriptive model, like expected utility is, see Schoemaker (1982). In our opinion there is no difference with respect to loss aversion, but probability weighting should not be present in a normative model of individual decision making.

The analysis in Chapter 6 deals with a model with loss aversion and decision weighting and computes the optimal decisions for economic agents with such

[1] This might be changed in future waves of the CSS. The data used by Shelley (1993), for example, do contain negative observed discount rates.

preferences. Before we can use decision weighting and loss aversion in serious empirical microeconomic research many open questions have to be answered. If we want to use direct information on the income distribution, we have to know whether respondents answer their subjective probabilities or the decision weights they use when they make their decisions. A second question is how individuals deal with the probability of dying. Is dying the worst possible outcome and weighted as such or is it an outcome that is handled separately and the probability distribution for all other possibilities is rescaled and transformed accordingly? The last option has been used in Chapter 6 and we think this is the most plausible way to deal with it.

For the application of loss aversion it is important to know what the reference point is, whether there are only reference points for, say, consumption, or whether there are also reference points for, for example, the level of wealth, like it is used in Barberis, Huang, and Santos (1999). Furthermore, there is one possibly important determinant of reference points that did not receive any attention in this thesis, which is the influence of reference groups or the individual's surroundings on the individual's well-being. Empirical evidence for the presence of the effect of reference groups is presented in Duesenberry (1949) and there is also evidence for this from laboratory experiments. Since we do not have precise knowledge about what the relevant reference points are, we will have to consider some alternatives, when we conduct empirical research. By trial and error we might learn what type of reference points are important and how they are formed.

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Samenvatting

De beslissingen van individuen en huishoudens spelen een belangrijke rol binnen de economie. Veel economen houden zich dan ook bezig met het verklaren en voorspellen van de beslissingen van individuen of huishoudens. Het onderzoek in dit proefschrift analyseert welke rol subjectieve informatie hierin kan spelen. Met subjectieve informatie bedoelen we informatie die niet op een andere manier verkregen kan worden dan door het aan het individu zelf te vragen. In dit proefschrift wordt specifiek aandacht besteed aan subjectieve informatie, die een rol kan spelen bij het nemen van economische beslissingen. Hierbij kan gedacht worden aan risico aversie en tijdsvoorkeur. De economische beslissingen die we onderzoeken zijn op te splitsen in twee groepen. De eerste groep heeft te maken met beslissingen die gerelateerd zijn aan de keuze om een huis te kopen. Allereerst gaat het hier om de keuze om te kopen of te huren. Voor de mensen die een huis kopen kijken we naar de waarde van het huis dat gekocht wordt en de hoogte van de hypotheek die opgenomen wordt. De tweede groep van economische beslissingen is de beslissing om risicovolle beleggingen te doen of niet.

In het algemeen kunnen we drie soorten subjectieve informatie onderscheiden. Dit betreft informatie over de huidige situatie van het individu, informatie over verwachtingen voor de toekomst en informatie over keuzes die een individu in bepaalde situaties zegt te zullen maken. De laatste soort informatie is informatie over individuele preferenties. Het belang van zulke subjectieve informatie komt voort uit het feit dat we niet voldoende objectieve informatie kunnen verzamelen om de preferenties van een individu te kunnen identificeren. Toekomstverwachtingen van een individu zijn per definitie subjectief, want deze zijn niet op een objectieve manier te achterhalen. Wanneer er subjectieve informatie aanwezig is in een dataset, dan kan deze informatie gebruikt worden om te corrigeren voor anders niet waargenomen heterogeniteit. In dit proefschrift zullen drie soorten van subjectieve informatie uitgebreid onderzocht worden. Het gaat hierbij om een maat voor tijdsvoorkeur, maten voor risicoaversie en een maat voor inkomensonzekerheid. Elk van deze gevallen van subjectieve informatie speelt een belangrijke rol in de economie. Tijdsvoorkeur is vooral van belang bij het maken van investeringsbeslissingen, waarbij je kunt denken aan de aanschaf van een huis, maar ook aan de keuze om langer naar school te gaan of te gaan werken. Risicoaversie speelt een rol bij de keuze van de manier waarop spaargeld belegd wordt. Zet iemand zijn geld simpelweg op een spaarrekening, of durft hij meer risico te nemen door het te investeren in beleggingsfondsen of aandelen? Inkomensonzekerheid heeft volgens de economische theorie invloed op de hoeveelheid spaargeld die mensen willen hebben. Het idee hierachter is dat als je minder zeker bent over je inkomen, je meer zult sparen om te zorgen dat je genoeg geld hebt wanneer het inkomen lager uitvalt.

Het proefschrift begint in Hoofdstuk 2 met de vraag of subjectieve informatie relevant kan zijn bij het verklaren van economische beslissingen. In dit hoofdstuk wordt aandacht besteed aan tijdsvoorkeur, risicoaversie en interesse in financiële zaken. De analyse wordt uitgevoerd met behulp van de Center Savings Survey (CentER Besparingen Panel), waarin een groot aantal vragen met betrekking tot subjectieve grootheden gesteld zijn. Ter illustratie zijn een aantal vragen opgenomen in een appendix bij deze samenvatting. Het hoofdstuk begint met te analyseren in hoeverre we deze vorm van informatie kunnen verklaren uit de traditioneel gebruikte objectieve informatie, zoals inkomen, geslacht, leeftijd en gezinsgrootte. Het blijkt dat we slechts een klein deel van de subjectieve informatie kunnen verklaren met behulp van objectieve informatie. Dit kan twee oorzaken hebben. Allereerst kan het zijn dat de antwoorden slechts 'lukraak' zijn en ze dus geen enkele nieuwe informatie bevatten. Het kan echter ook zo zijn dat het juist wel informatie geeft, die we voorheen nog niet hadden, want anders hadden we de antwoorden wel kunnen verklaren. Om te onderzoeken of de vragen echt nieuwe informatie bevatten kijken we of er verbanden bestaan tussen de subjectieve informatie en daadwerkelijke beslissingen van mensen. We kijken hierbij specifiek naar de keuze van de respondenten in het panel om een huis te kopen of te huren en als ze een huis gekocht hebben, hoe duur dat huis was en hoeveel hypotheek ze opgenomen hebben in verhouding tot de waarde van het huis. Als laatste kijken we naar de beslissing om risicovolle beleggingen te doen met de beschikbare financiële middelen.

Tijdsvoorkeur heeft in dit proefschrift te maken met de afweging tussen het heden en het verleden. We gebruiken hiervoor de term ongeduldig, waarbij iemand die ongeduldiger is, meer bezig is met het heden dan met de toekomst, in verhouding tot een geduldiger iemand. Over het effect van tijdsvoorkeur op de beslissing om een huis te kopen voorspelt de economische theorie dat mensen die ongeduldiger zijn een kleinere kans hebben om een huis te kopen. De redenering hierachter is dat zulke mensen liever niet nu de grote aanschaf doen, die pas op langere termijn voordelen oplevert. Hoe geduldiger mensen zijn, des te meer nadruk zullen ze leggen op de toekomstige voordelen en des te groter is de kans dat zij dus een huis kopen. In het econometrische model dat we schatten komt dit ook duidelijk naar voren. Het effect van de subjectieve maat voor tijdsvoorkeur is hetzelfde als het effect dat de economische theorie voorspelt voor tijdsvoorkeur. Dit geeft ons vertrouwen dat subjectieve informatie over tijdsvoorkeur relevant kan zijn bij het verklaren en voorspellen van economische beslissingen.

De subjectieve maat voor risicoaversie die we gebruiken in dit hoofdstuk speelt geen belangrijke rol in de verklaring van de beslissingen die met het huis te maken hebben. Het enige effect is dat meer risicoaverse mensen over het algemeen een goedkoper huis kopen. Wanneer we kijken naar de beslissing om risicovolle investeringen te doen, speelt risicoaversie een hele grote rol. De kans dat mensen risicovolle investeringen doen, wordt kleiner naarmate ze meer risicoavers zijn. Ook hier concluderen we dus dat subjectieve informatie over risicoaversie nieuwe informatie oplevert die een rol kan spelen bij het verklaren van economisch gedrag.

Deze eerste resultaten omtrent het nut van subjectieve informatie zijn heel bemoedigend en geven aanleiding om serieuzer te kijken naar de manier waarop men aan de economische theorie gerelateerde subjectieve informatie het beste zou kunnen meten en hoe ze gerelateerd zijn aan objectieve informatie. Het is niet alleen interessant om te weten hoe risicoavers mensen zijn, maar het is ook interessant om bijvoorbeeld te weten of oudere mensen nu meer of minder risicoavers zijn dan jonge mensen en of mannen meer risicoavers zijn dan vrouwen.

In Hoofdstuk 3 analyseren we de inkomensverwachtingen van de respondententen. Om informatie over de mogelijke hoogtes van het inkomen in het komende jaar te verkrijgen wordt allereerst gevraagd wat het laagst en hoogst mogelijke inkomen voor het komende jaar is. Daarna worden voor bepaalde inkomensniveaus binnen deze grenzen gevraagd wat de kansen zijn dat het inkomen onder elk van die niveaus ligt. Met deze informatie leiden we een inkomensverdeling af en hieraan gerelateerd een maat voor de hoogte van het inkomen (de mediaan van de verdeling) en een maat voor de relatieve inkomensonzekerheid (de verhouding tussen de interkwartiel afstand en de mediaan van de verdeling). Zoals te verwachten is, hangt de hoogte van het inkomen sterk af van het inkomen dit jaar, waarbij wel grote verschillen te vinden zijn tussen één- en twee-verdieners. Voor inkomensonzekerheid valt het op dat veranderingen in het verleden niet tot een grotere inkomensonzekerheid leiden. Wanneer men echter verwacht dat de huidige arbeidsmarktsituatie gaat veranderen, leidt dit wel tot meer inkomensonzekerheid. Het laatste onderdeel van Hoofdstuk 3 is een vergelijking van de inkomensonzekerheid in de Verenigde Staten, Italië en Nederland. Hieruit blijkt dat Amerikanen de grootste inkomensonzekerheid hebben en dat in Italië de inkomensonzekerheid iets kleiner is dan in Nederland.

Hoofdstuk 4 behandelt het meten van risicoaversie met behulp van keuze vragen die gaan over loterijen. Twee typen vragen kunnen hier worden onderscheiden, zijnde vragen waarbij men moet kiezen tussen twee loterijen en vragen waarbij men de kans op een prijs in één van de twee loterijen moet vaststellen, zodanig dat men indifferent is tussen de twee loterijen. De antwoorden op deze vragen worden op twee manieren geanalyseerd. In eerste instantie relateren we de antwoorden op de vragen aan objectieve informatie, zonder veel structuur te leggen op de relatie tussen de objectieve informatie en de antwoorden. Dit gebeurt met een semiparametrisch model voor iedere vraag. Op basis hiervan vinden we dat opleidingsniveau en inkomen een negatieve relatie hebben met risico aversie en dat vrouwen meer risico avers zijn dan mannen. Het nadeel van deze methode is echter dat we alleen maar een ordening in de mate van risico aversie als resultaat hebben. We kunnen hiermee niet voorspellen wat iemands antwoord zou zijn op een andere vraag. Om dit wel te kunnen, moeten we meer structuur opleggen.

Het tweede deel van Hoofdstuk 4 behandelt een structureel model dat precies beschrijft hoe mensen vragen omtrent risico aversie beantwoorden. Uit reeds eerder in de literatuur beschreven experimenten is gebleken dat het model van verwachte nutsmaximalisatie geen goede verklaring geeft van de antwoorden van mensen op vragen over onzekere uitkomsten. Om deze reden baseren we het empirische model op een algemenere theorie, namelijk Cumulative Prospect Theory.

Het verschil tussen deze twee theorieën is dat Cumulative Prospect Theory toelaat dat mensen niet de echte kansen op de uitkomsten als gewichten gebruiken, maar dat ze de meer extreme uitkomsten meer gewicht geven dan op basis van de echte kans gerechtvaardigd is. Een tweede verschil tussen Cumulative Prospect Theory en de meer traditionele aanpak is dat de uitkomsten afzonderlijk bekeken worden en niet gecombineerd worden met de huidige situatie. Dit fenomeen wordt algemeen aangeduid met de term referentiepuntafhankelijkheid. De waardering voor een uitkomst hangt af van het referentiepunt dat men heeft. Een slechte uitkomst kan nog steeds als positief ervaren worden, zolang de uitkomst maar beter is dan was verwacht. De resultaten geven duidelijk aan dat ook bij de door ons gebruikte vragen Cumulative Prospect Theory een beter beschrijving geeft van de antwoorden dan verwachte nutsmaximalisatie. Er is echter weinig systematische variatie in de mate waarin respondenten kansen herwegen.

Bijna alle economische beslissingen hebben gevolgen voor meer momenten in de tijd. Over het algemeen wordt aangenomen dat mensen verschillende gewichten geven aan gebeurtenissen op verschillende momenten in de tijd, waarbij deze gewichten lager zijn voor tijdstippen verder in de toekomst. Mensen zijn ongeduldig en ontvangen iets positiefs liever vandaag dan over tien jaar. In Hoofdstuk 5 worden de antwoorden op zestien vragen geanalyseerd, die gaan over het betalen van belasting of over het ontvangen van een gewonnen prijs op verschillende momenten in de tijd. De reden dat er zo veel vragen gebruikt zijn, is dat uit eerder onderzoek is gebleken dat de manier waarop de vraag geformuleerd is van grote invloed is op het antwoord, ook al gaat de vraag vanuit economisch oogpunt wel over een soortgelijke situatie. Het blijkt een groot verschil te maken of men de afweging maakt tussen nu of volgend jaar een gewonnen prijs in een loterij te ontvangen of tussen nu of volgend jaar een belastingaanslag te betalen. Binnen de economische theorie is het echter zeer moeilijk om dergelijk gedrag te rationaliseren of te motiveren. Binnen de economische psychologie is er echter een model ontwikkeld dat, net als het model in Hoofdstuk 4, gebruik maakt van een referentie punt en dat mogelijkerwijs wel in staat is om de verschillen tussen de verschillende vragen te verklaren zonder dat de afweging tussen het heden en de toekomst op een andere manier gebeurt. Het is de eerste keer dat een dergelijk model geïmplementeerd wordt in een praktische toepassing en het blijkt dat het model een goede verklaring van de data geeft. Een groot verschil met eerder onderzoek is dat in ons onderzoek mensen nauwelijks ongeduldig blijken te zijn, terwijl soortgelijke data voorheen werden geïnterpreteerd als bewijs voor een hoge mate van ongeduld bij mensen. Ook in dit model is toegelaten dat mensen met verschillende achtergrondkenmerken een andere mate van tijdsvoorkeur hebben. Hieruit blijkt dat vrouwen en oudere mensen meer geduld hebben dan mannen en jonge mensen. Verder hebben mensen met een hoger inkomen ook meer geduld.

De analyse in Hoofdstukken 4 en 5 laat zien dat het traditionele economische model misschien niet zo'n goede beschrijving geeft van de manier waarop mensen vragen over risico aversie en tijdsvoorkeur beantwoorden. In Hoofdstuk 6 kijken we of de binnen de economische psychologie ontwikkelde modellen voor zulke hypothetische vragen ook een betere verklaring kunnen geven voor meer algemene economische vraagstukken. We gaan hierbij specifiek in op een speciaal vraagstuk binnen de economie waarop nog geen algemeen aanvaard antwoord is gevonden. Dit vraagstuk is het aandelenoverprijzingsvraagstuk (equity premium puzzle). Met het traditionele model is het niet mogelijk om het grote verschil tussen de verwachte rendementen op risicovolle beleggingen en relatief veilige beleggingen te verklaren zonder een enorm hoge mate van risico aversie te veronderstellen.

Uitgaande van de modellen gebruikt in Hoofdstukken 4 en 5 modelleren we het gedrag van economische agenten als volgt. Ze maximaliseren een gewogen toekomstig nut, waarbij de weging niet plaats vindt met de objectieve kansen, maar met getransformeerde kansen. Verder hangt het nut van consumptie niet alleen af van de hoogte van de consumptie, maar ook van het verschil in consumptie met de vorige periode. Het idee hierachter is dat mensen het niet prettig vinden om achteruit te gaan in hun consumptieniveau. Het berekenen van optimaal gedrag voor dergelijke economische agenten kost veel rekentijd op een computer. Om deze reden wordt alleen gekeken naar het optimale gedrag volgens het model voor een klein aantal parameter specificaties om te zien wat voor soort gedrag resulteert. We gebruiken geen echte data om de parameters in het model te schatten.

De resultaten van dit model zijn positief over de mogelijkheid om het aandelenoverprijzingsvraagstuk te verklaren. Het effect van de afkeer van verlies, wat is gemodelleerd door naast het niveau van consumptie ook het verschil in consumptie met de vorige periode mee te nemen, voor de verklaring van het vraagstuk is gering, maar de toepassing van kansweging bij het bepalen van de optimale beslissingen heeft wel grote gevolgen voor de optimale investeringen in risicovolle en risicovrije beleggingen. Mensen willen gegeven de hoge verwachte rendementen toch niet zo veel in risicovolle beleggingen investeren. Hieruit kan men afleiden dat de hoge rendementen niet in tegenspraak zijn met het beslissingsmodel van de economische agenten. Ook al kost het meer moeite, toch is het dus de moeite waard om te kijken naar meer gecompliceerde beslissingsmodellen voor economische agenten, want zulke modellen lijken betere beschrijvingen te kunnen geven voor de economische fenomenen, die we in deze wereld zien.

Appendix

Tijdsvoorkeur vragen

1. Stelt u zich voor dat u een aanslag krijgt voor achterstallige belastingen. Voor de betaling kunt u kiezen uit twee mogelijkheden. De ene mogelijkheid is dat u NU f 1000,- betaalt. De andere mogelijkheid is dat u pas LATER betaalt, maar dan moet u ook MEER betalen. Wat kiest u?

Ik betaal f 1000,- nu

of

Ik wacht 3 maanden met de betaling en wil hiervoor extra betalen

Als men bereid is om extra te betalen voor het uitstel, wordt de volgende vraag gesteld:
Hoeveel gulden wilt u voor de wachttijd van 3 maanden bovenop de f 1000,- MAXIMAAL EXTRA betalen?

2. Stelt u zich voor dat u een geldprijs wint in een loterij. De prijs bedraagt f 1000,- en kan DIRECT worden geïnd. Veronderstel dat de loterij, een financieel betrouwbare organisatie, u verzoekt 3 maanden te wachten voordat u de prijs krijgt. Zou u met dit voorstel akkoord gaan of zou u om meer geld vragen als u 3 maanden moet wachten?

Ik stem in met de wachttijd van 3 maanden en hoef hiervoor geen extra geld te ontvangen. Na 3 maanden ontvang ik dus f 1000,-

of

Ik stem in met de wachttijd van 3 maanden, maar wil hiervoor extra geld ontvangen

Als men bereid is te wachten voor een extra vergoeding, wordt de volgende vraag gesteld:
Hoeveel gulden wilt u voor de wachttijd van 3 maanden als aanvulling op de f 1000,- MINIMAAL EXTRA ontvangen?

Risico aversie vragen

1. Ik vind het belangrijker veilig te beleggen en een gegarandeerd rendement te krijgen dan risico te nemen in de hoop het hoogste rendement te krijgen.

Mee eens 1 2 3 4 5 6 7 Mee oneens

2. Veronderstel dat u f 200,- in een spel gewonnen hebt. U kunt nu kiezen tussen een bedrag van f 200,- vast in handen en een lot dat u een bepaalde kans biedt om een prijs van f 20.000,- te winnen.
Hoe groot moet dan de kans zijn op de f 20.000,- om het lot te kiezen in plaats van de f 200,- vast in handen?

Ik zou het lot verkiezen als de kans op de hoofdprijs minimaal gelijk is aan .....

3. Hoe zoudt u kiezen tussen de volgende twee mogelijkheden?

   1. U trekt een lot met een kans van 2 procent dat u f 3000,- wint (indien u verliest, krijgt u niets)

   2. U trekt een lot met een kans van 1 procent dat u f 6000,- wint (indien u verliest, krijgt u niets)

Inkomensonzekerheid vragen

1. We willen graag nog wat weten over uw verwachtingen wat betreft het totale netto-inkomen van uw huishouden voor de komende 12 maanden. Wat denkt u dat het LAAGSTE bedrag is dat het totale netto-inkomen van uw huishouden de komende 12 maanden kan bereiken?

Vervolgens worden een aantal vragen van het volgende type gesteld:

2. Hierna ziet u een aantal mogelijke bedragen voor het totale netto-inkomen van uw huishouden. Kunt u bij elk van deze bedragen aangeven wat de kans is (uitgedrukt in procenten (of hoeveel gevallen uit 100)) dat het totale netto-inkomen van het huishouden de komende 12 maanden MINDER zal zijn dan het aangegeven bedrag.

Hoe groot acht u de kans dat het totale netto-inkomen van uw huishouden de komende 12 maanden MINDER zal zijn dan x gulden? Vult u een getal in van 0 t/m 100.

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BAS DONKERS graduated in econometrics from Tilburg University. In December 1995, he started his Ph.D. project at the Department of Econometrics at the same university. His main interests lie in the modeling of individual decision making processes and in the application of advanced econometric techniques. Since February 2000, he is working at the Department of Marketing and Organization at Erasmus University in Rotterdam.

Economists have been rather skeptical towards the use of subjective information. This thesis shows that this type of information can be relevant for the empirical explanation of economic decisions. Three examples of subjective information, which are time preference, income uncertainty, and risk aversion, are studied extensively in this thesis. The models used in the analyses of the subjective information are based on models developed by economic psychologists. These models are different from the traditional discounted expected utility model most often used in economics. The major differences are the presence of loss aversion and probability weighting. An economic model that incorporates these differences is used to explain the equity premium puzzle.

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