On income expectations and other subjective data

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On Income Expectations

and

Other Subjective Data:

A Micro-Econometric Analysis

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A Micro-Econometric Analysis

Proefschrift

ter verkrijging van de graad van doctor aan de Katholieke Universiteit Brabant, op gezag van de rector magnificus, prof. dr. L.F.W. de Klerk, in het openbaar te verdedigen ten overstaan van een door het college van decanen aangewezen commissie in de aula van de Universiteit op

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door

Johannes Wilhelmus Maria Das

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PROMOTORES: Prof. dr. B.B. van der Genugten
Prof. dr. A.H.O. van Soest

Voor mijn ouders en Gerrie

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The last sentence is reserved for another important person in my life. Gerrie, thank you for your patience, love, and constant support.

Marcel
November 1997

Contents

Chapter 1

Introduction

1.1 Motivation

Expectations about the future are central to economic models of behavior. Famous theories like the Permanent Income Hypothesis and the Life Cycle Theory embody the idea that individuals or households are forward looking decision makers. Consumption is then determined not only by disposable income, but also by the future income stream. Based on their current and future income distribution, individuals decide how much to spend on current consumption and how much to add to their current assets.

Being unable to look in the decision makers' minds and see what they expect, one has to make assumptions on how expectations are formed. The importance is stressed by Svendsen (1993): "In economic theory the question on how expectations are formed has long been seen as crucial to the question on how the economy works." The most widely used model for the expectations process is the hypothesis of rational expectations. The rational expectations hypothesis was first proposed by Muth (1961).[1] In the last few decades several forms of the hypothesis were used in both theoretical and empirical studies. It is, therefore, rather difficult to give a precise definition, but in the most common formulation the rational expectations hypothesis assumes that the individual uses all the available information to form an expectation about a future variable efficiently: "... rational expectations, that is, expectations equal to the mathematical expectations of y_{t+1} based on the information available at

[1] According to Muth, an expectation is said to be rational if it is the optimal point forecast based on the observation of some economic variables, and on the true model linking these variables and the predicted variables.

time t" [Blanchard and Fischer (1989)]. More generally, since the whole income distribution might be involved in the economic model of interest, the above formulation also fits for expectations of higher moments of y_{t+1} (for instance, the mathematical expectation of y_{t+1}^2, given the information available at time t).

After the theory on rational expectations has been formulated, many researchers have tried to test the hypothesis [see, for instance, Zarnowitz (1985), Ivaldi (1992), and Hey (1994)]. Lovell (1986) gives an early review of the literature on empirical tests of the rational expectations hypothesis. The empirical evidence is mixed: some reject, and some are in favor of the rational expectations hypothesis.

In general, there are two methods to test expectations hypotheses: the direct and the indirect method. The indirect method specifies an explicit model of how expectations are formed. Economists prefer this indirect method also in estimating models of economic behavior, when the primary goal is not testing the explicit model of expectations formation. In a life cycle framework, the standard approach is to infer income expectations from panel data on realizations [see, for instance, Hall and Mishkin (1982) and Carroll (1994)].

The major disadvantage of the indirect method is the necessity to rely on the model for the expectation formation. One starts with an economic model including the individuals' expectations and makes assumptions on how these expectations are formed. The implications of combining the expectations hypothesis and a specific economic theory underlying the model, are then tested empirically. Since the hypotheses to be tested are joint hypotheses, one cannot conclude whether one has to reject the process of expectation formation or whether one has to reject it only in combination with the assumed economic model (if one rejects at all).

A method that does not have this disadvantage is the direct method. The direct method observes the individuals' expectations by just asking them what they expect. Although there is no need to specify any underlying economic model, the direct method is less popular among economists. The skepticism is based upon the assertion that people have no incentive to answer the questions carefully. But Dominitz and Manski (1997) rightly argue that if this is to be taken seriously, it should be applied to survey data on realizations and not just exclusively to subjective data. Empirical economic analyses of household behavior routinely use self-reports on realized income, assets, employment, and other variables.

The fact that subjective data can eliminate the need to formulate a process of expectations formation is not the only reason that they can be useful in economics. In estimating household equivalence scales,[2] for example, subjective data give a feasible solution to the identification problem as pointed out by Pollak and Wales (1979). Recent applications in this area that make use of subjective data are Melenberg and Van Soest (1995) and Charlier (1997). The former use a cross-section that contains two types of subjective data for the same households, and the latter uses panel data on subjective data to estimate household equivalence scales. Also in studies concerning interdependent preferences [see e.g. Manski (1993)] and poverty line definitions, subjective data can help to solve identification problems. Especially in the latter field, numerous publications by Dutch researchers, in particular, have appeared. An early overview is given by Wansbeek and Kapteyn (1985) [for more recent references see, for example, Van Praag (1991) and Kapteyn (1994)].

1.2 Overview of the thesis

This thesis focuses on subjective data, in particular on answers to questions on income growth expectations. We do not aim to use these answers in explaining economic models of household behavior, but place the emphasis more on the reliability and usefulness of the subjective data. Apart from in Chapter 6, we use two Dutch panels. The first is the Dutch Socio-Economic Panel (SEP), which is administered by Statistics Netherlands. The SEP is representative of the Dutch population, excluding those living in special institutions such as nursing homes. The first survey was conducted in April 1984. The same households were interviewed in October 1984 and then twice a year (in April and October) until 1989. Since 1990, the survey has been conducted once a year in May. In the October interview, information is collected on socio-economic characteristics, income, and labor market participation. This thesis focuses on the waves of 1984 through 1989, because in 1990 the questions related to (actual) income changed substantially.

The second panel that is used in this thesis is the VSB panel. The VSB panel was devised by researchers at CentER for Economic Research at Tilburg University and has been supported by the VSB Foundation. One part is representative of the Dutch population, whereas the other part sampled the wealthier households. The VSB panel started in 1993, and the survey method is completely computerized. This

[2] A household equivalence scale is defined as the ratio between family incomes needed to attain a given utility level for the family of interest and some reference family. They can be used to compare utility levels of households with different compositions.

thesis considers only the wave of 1995, since in this wave the answers to the questions we will use were collected for the first time.

Chapter 2, largely based on Das and Van Soest (1997), analyzes direct subjective information on expected changes of household income in one panel wave of Dutch families. Data come from the first wave of the SEP (October 1984). First we describe the answers to questions on expectations about future income growth. We present some nonparametric regressions of these expectations on age and actual income to suggest appropriate parametric models. Further, we investigate how the expectations can be explained by income changes in the past and other variables. For this purpose we use an ordered response model – since our dependent variable is of an ordered discrete nature. Second, we compare the expected income changes to the realized income changes of the same individuals, exploiting the panel nature of the SEP. It seems reasonable to assume that the head of household has the same concepts in mind while answering questions on expected and realized household income growth. Moreover, the question on expectations immediately follows after the question on realizations. Assuming that no macro-economic shock has taken place, this indicates to what extent people systematically under- or overestimate their income growth.

A major critique to the analysis in Chapter 2 is that its findings might be sensitive to the point in time taken. The results, for example, might be influenced by the presence of macro-economic shocks. A check of robustness is carried out at the end of the chapter, but there we only use the next couple of waves of the SEP. A more careful analysis is carried out in Chapter 3, where we fully exploit the panel nature of the SEP. The analysis in this chapter is based upon the waves of October 1984 through October 1989.

Chapter 3, virtually identical to Das and Van Soest (1996), uses models that are extensions of existing binary choice panel data models to the ordered response case. The models allow for the incorporation of individual specific effects. We consider random and fixed individual effects models. The extension in the random effects case is rather straightforward. In the fixed effects case, we use the conditional likelihood approach by Chamberlain (1980) after aggregating adjacent categories to two categories. The final estimator is then obtained by combining the estimates for separate aggregations of categories with a minimum distance procedure.

The SEP also contains detailed information on income from about twenty potential sources for each individual. An objective measure of after-tax household income can then be constructed by adding up all income components of the family members and some specific household components (such as child benefits). This gives us the opportunity to compare an objective measure of household income growth with the subjective answer to the question on realized income change. Such a comparison is carried out in Chapter 3 for all the waves under consideration.

The data we use in Chapters 2 and 3 are, as in most studies with subjective data, of a qualitative nature. The simplest form of predictions questions are those that call for yes/no predictions of binary outcomes. The usefulness of such questions has been a topic of debate over the last 50 years. The history of eliciting consumers' subjective expectations in the U.S. has been summarized by Dominitz (1994). By the mid-60s, opinion among mainstream economists was firmly negative.

Manski (1990) formalized one critique of using qualitative data. His article studies the relationship between stated intentions and subsequent behavior under the hypothesis that individuals have rational expectations and that their responses to intentions questions are the best predictions of their future behavior. He places an upper bound on the behavioral information contained in intentions data. His argument could be summarized in an example as follows. Suppose we have a group of Ph.D. students who are asked whether or not they expect to become a full professor within the next ten years. A possible model for the answer to this question is: "yes", if their subjective probability exceeds 0.5, and "no" otherwise. Since all of them (think they) are intelligent – the subjective probability of each student is 0.6 – they will answer "yes". In general, however, part of the group will not become full professors. If the subjective distributions of the future variables are correct, only 60% will become full professors. The reason is that the expectation reflects some location measure of the household's subjective distribution, while the outcome is based upon one draw of the actual distribution. Even in the case that subjective and actual distributions coincide, the two variables are not directly comparable.

One could aim this critique also at the comparison of expected and realized income growth as studied in Chapters 2 and 3. Chapter 4 will analyze this in more detail. Chapter 4 appeared as Das et al. (1997) and extends Manski's analysis to the case of more than two outcomes. We derive bounds for conditional probabilities of outcomes given predictions that should be valid under the hypothesis of rational expectations. The bounds are derived under each of three different response models generating best predictions of the prospective outcomes. Each model is based on a different expected loss function which respondents are assumed to minimize. We then repeat the comparisons of expected and realized income.

Another, more sophisticated way of eliciting respondents' subjective distribution of future income is studied in Chapter 5, which is based on Das and Donkers (1997). As recognized by Juster (1966), expectations questions can be improved upon by asking the respondent to give his or her probability for the future outcome. Inspired by empirical studies conducted by Guiso et al. (1992) and Dominitz and Manski (1997), the VSB panel started in the third wave to collect detailed information on the subjective future income distribution. The main focus of Chapter 5 is to use this information to construct a (subjective) measure of income uncertainty.

Future income uncertainty has an impact on several decisions households make. Carroll (1994) finds in an empirical study that consumers facing greater income uncertainty consume less. In the literature on precautionary saving, several papers have addressed the theoretical result that consumers postpone their consumption when income becomes risky. See e.g. Guiso et al. (1992), Lusardi (1993), and Banks et al. (1995). Portfolio decisions may also be affected by income uncertainty. At an empirical level, this is illustrated by Guiso et al. (1996) and Hochgürtel (1997). Most of the empirical studies, in which income uncertainty is involved, face the problem of measuring this uncertainty. Direct measurement of households' perceived uncertainty may provide us with a solution.

The 1995 wave of the VSB panel contains two blocks of questions related to the measurement of subjective income uncertainty. The first one consists of qualitative questions. Chapter 5 briefly describes the qualitative measurement, but the main focus is on the second block of questions eliciting income uncertainty in a quantitative way. First respondents are asked to indicate the range of their future income distribution and after that, they are asked to evaluate the probability with which their household income will fall below a certain level (in the indicated range). Although this type of individual specific question is, in principle, possible in the more traditional handwritten questionnaires, the computerized survey method used in the VSB panel is a rather efficient way of asking this.

On the basis of the given probabilities, we derive subjective cumulative income distributions for each head of household from which a measure of income uncertainty is obtained. We compare this measure of income uncertainty with corresponding studies conducted in the U.S. and Italy. In addition, we examine how our measure of income uncertainty varies with some household characteristics. A possible correlation can yield useful information. First, 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. Second, if a relationship exists, this information might be useful for studies in which no subjective data are available.

The next chapter, Chapter 6, differs from the previous chapters in that it focuses neither on income expectations nor income uncertainty. Rather, it concentrates on a methodological issue with respect to ordered response models. In the cross-section analysis of Chapter 2 we use such a model in which the observed categorical income change is based upon classifying an underlying unobserved variable into one out of a finite number of intervals. The thresholds of the intervals are (unknown) real-valued parameters – the same for every individual. The assumed constancy of the threshold parameters can be relaxed by allowing the thresholds to be a linear function of observed explanatory variables [see Terza (1985)]. Chapter 6, which is based upon Das (1995), extends the standard ordered response model with deterministic thresholds by allowing for random thresholds that vary across individuals. The underlying unobserved variable will then be classified according to a random dissection of the real line. This extension is the main focus of Chapter 6. The methodology is applied to a data set focusing on consumer valuation of new products. Although this application has limited economic relevance, it serves well as an illustration of the proposed extension.

Chapter 7 summarizes the main results of this thesis. Based on these results, we will provide some overall conclusions. In addition, we give some indications for future research.

Chapter 2

Expected and Realized Income Changes

Income expectations play a central role in household decision making. In the life cycle model, for example, consumption and savings decisions reflect expectations of future income. In empirical applications in which direct information on expectations is not available, it is usually assumed that expectations are rational, and reflected by observed future realizations. This chapter analyzes direct subjective information on expected changes of household income in one panel wave of Dutch families. First, we describe these data and investigate how the expectations can be explained by, among other variables, income changes in the past. Second, we combine these data with information on realized income changes in the next panel wave, and analyze the differences between expected and realized changes. We find that, on average, households significantly underestimate their future income changes. This holds in particular for those families whose incomes have fallen in the past.

2.1 Introduction

In the dynamic process of household decision making, future expectations play a central role. In a life cycle framework, decisions on current consumption of nondurables and durables, housing, savings, portfolio choice, labor supply, etc., depend not only on current wealth, income and preferences, but also on the individual's or household's subjective distribution of family income, prices, and other input variables [see, for example, Deaton (1992)]. Most of the empirical literature on life cycle models don't use direct information on future expectations. To quote Dominitz and Manski (1997): "Skeptical of subjective data of all kinds, economists do not ordinarily collect data on income expectations. Instead, the standard approach is to infer expectations from panel data on realizations." [1] To estimate the life cycle model, it is then assumed that individuals' subjective expectations bear some relation to income realizations. This leads to the assumption of rational expectations, or to some alternative explicit model of expectation formation, estimated on the basis of realized incomes. [2]

Notable recent exceptions to this approach are, for example, Guiso et al. (1992, 1996), Lusardi (1993), and Alessie and Lusardi (1997). These papers use characteristics of subjective income distributions directly derived from survey data as explanatory variables to explain consumption, savings or portfolio choice. In line with this, interest in data on and the modelling of income expectations has increased. See Guiso et al. (1992), Dominitz and Manski (1997), and Alessie et al. (1997). [3] The former two analyze data on subjective income distributions on the basis of a cross-section. They do not compare income expectations with income realizations. The latter use panel data and show that expected changes in income are significantly correlated with actual income changes.

Our approach is in line with Dominitz and Manski (1997) and Alessie et al. (1997). We do not analyze consumption or savings, but focus on income expectations and realizations. We use the same subjective data on actual and expected income changes as Alessie et al. (1997), drawn from the Dutch Socio-Economic Panel (SEP). These questions are as follows:

A: Did your household's income increase, decrease, or remain unchanged during the past twelve months? Possible answers: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).

B: What will happen to your household's income in the next twelve months? Possible answers: see A.

[1] See, for example, Hall and Mishkin (1982) and other references in Dominitz and Manski (1997).

[2] For example, Carroll (1994) uses two methods for estimating future income of individuals participating in the 1960-1961 *Consumer Expenditures Survey* (CEX). In the first method, he estimates age/income cross-sectional profiles using household characteristics. A particular household's expected future income is then assumed to be given by the average observed income of older households with similar characteristics. The second method regresses actual 1969-1985 income on 1968 personal characteristics using data from the *Panel Study of Income Dynamics* (PSID).

[3] Carroll et al. (1994) use a macro-economic measure of economic prospects, the Index of Consumer Sentiment, and find that it positively affects consumer spending.

These questions are not very well specified. It is not clear whether nominal or real income is referred to, and it is not clear what distinguishes strong increases from increases, etc. We will come back to this in Section 2.4. The value of the questions is found in the fact that they are comparable: it seems reasonable to assume that the household has the same concepts in mind while answering questions A and B. Moreover, these questions have been asked at each wave of the panel, and it is possible to compare the expectation (B) in one year to the realization (A) the next year. In case of rational expectations and in the absence of macro-economic shocks, the distributions of these two should be similar. If not, then this would be evidence against crucial assumptions underlying the empirical work on life cycle models: either rational expectations, or the absence of macro-economic shocks, or both.

The organization of this chapter is as follows. Section 2.2 discusses the data, drawn from the SEP wave of October 1984. We describe the data on income change expectations (answers to question B) and present some nonparametric regressions of these expectations on age and actual income, used to suggest appropriate parametric models. Section 2.3 estimates an ordered response model explaining expected income changes from income changes in the past (question A), the level of actual income, and other background variables, such as age, family composition, and labor market status. Section 2.4 compares the expectations (question B) in 1984 with the realizations (question A) in 1985 of the same households, exploiting the panel nature of the SEP data. We investigate to what extent people systematically under- or overestimate their income changes. For this purpose, we consider an ordered response model, explaining the difference between realization and expectation, using the same explanatory variables as in Section 2.3. At the end of the section we briefly comment on the validity of rational expectations and the presence of macro-economic shocks. Section 2.5 summarizes our findings.

2.2 Description of the data

Data were taken from the Dutch Socio-Economic Panel (SEP), which is administered by Statistics Netherlands (CBS). The SEP is a random sample of the Dutch population, excluding those living in special institutions such as nursing homes. [4]

For this section, we use the wave of October 1984 to elicit information on expected

[4]See CBS (1991) for details about contents, setup, and organization of the SEP.

future income changes. Heads of households are asked to answer question B (see Section 2.1). The answer to this question will be denoted by INCEXP. This differs from the way in which Dominitz and Manski (1997) collected their data. Their income-expectations questions took the form: "What do you think is the percent chance (or what are the chances out of 100) that your total household income, before taxes, will be less than Y over the next 12 months?". With the responses to a sequence of such questions for different values of Y, Dominitz and Manski (1997) estimate each respondent's subjective probability distribution for the next year's household income.

Dominitz and Manski compare their study with that of Guiso et al. (1992). Guiso et al. asked households to attribute weights, summing up to 100, to given intervals of nominal earnings percentage increases one year ahead. Carroll (1994), however, argues that it is clear that many households did not understand the survey question, since a very large proportion of households reported point expectations for the next year's income: in the survey used by Guiso et al., 34% of the households reported a degenerate subjective distribution. Carroll (1994) also notes that a substantial proportion of the population reported point expectations for the aggregate inflation rate. Though some households may know in advance what their household income will be, they cannot know with certainty what the aggregate inflation rate would be. Thus the case that households did not understand the question is fairly strong. Lusardi (1993) explains the point expectations, arguing that with a one-year time horizon, people may attribute non-negligible weights to a much smaller set of events than when considering the entire period of life until retirement. With a short time horizon, it is therefore not surprising that many households know with certainty their future nominal income.

The nature of our data does not allow us to estimate complete subjective probability distributions of respondents, and this is not our goal. We interpret INCEXP as an indicator that is positively correlated with the location of the subjective future income distribution. We try to explain differences in INCEXP across families from a number of variables. One of them is related to an income change in the past: the answer to question A (see Section 2.1), which will be represented by the variable PREV_84.

The original SEP wave of October 1984 contains 3787 households. Since we use actual household income as an explanatory variable, we removed all households for which at least one component of household income was missing. In particular, this implied removing most households with self-employed members, who usually did not provide reliable information on their incomes. We also removed a few observations with missing information on other explanatory variables. This reduced the data set to 2729 observations. Removing observations for which INCEXP or PREV_84 was missing, we finally arrived at a total number of 2683 households.

In Table 2.1 we display a bivariate frequency table of INCEXP and PREV_84. Note that both variables refer to income changes, not to income levels.

Table 2.1 : Bivariate frequencies (in %) of INCEXP and PREV_84

PREV_84 → INCEXP ↓	1	2	3	4	5	total
strong increase: 1	3.0	1.0	1.6	0.1	0.1	5.9
decrease: 2	5.4	15.1	11.5	0.7	0.5	33.1
no change: 3	2.7	7.6	33.8	4.8	1.4	50.3
increase: 4	0.6	0.9	4.5	3.4	1.0	10.3
strong increase: 5	0.0	0.1	0.1	0.1	0.1	0.4
total	11.7	24.6	51.6	9.0	3.1	100.0

Most of the households (50.3 percent) do not expect their current income to change. This is in line with Dominitz and Manski (1997), who find that realized household income is the dominant predictor of expected future household income. More striking is that about 39.0% expect an income decrease, while only 10.7% expect an income increase. [5] To a lesser extent, the same is true for the realized household income in the previous twelve months (36.3% and 12.1%, respectively). 55.4% of the households expect that the change in income this year will fall in the same category as it fell last year. Finally, note that the dispersion in expected income changes is much smaller than in realized income changes. In particular, the number of families expecting a change is about the same as the number of families which have experienced a change, but there are few households who expect a large increase or a large decrease. In terms of expected income levels, this suggests that the expected level is determined by the current level and an (incomplete) adjustment in the direction of last year's change.

[5] Similar results are obtained using a different data source: according to the CBS (1993), the fraction of families in 1984 expecting that their financial situation will worsen, is about 20 percent points higher than the fraction expecting an improvement.

This seems to be an important refinement of Dominitz and Manski's finding, who only use information on income levels and not on income changes.

To suggest and motivate appropriate parametric models, we present some nonparametric regressions of INCEXP on age and actual after-tax family income. [6]

Figure 2.1 : Nonparametric regression of income expectation (INCEXP) on age with 95% uniform confidence bounds (dashed lines)

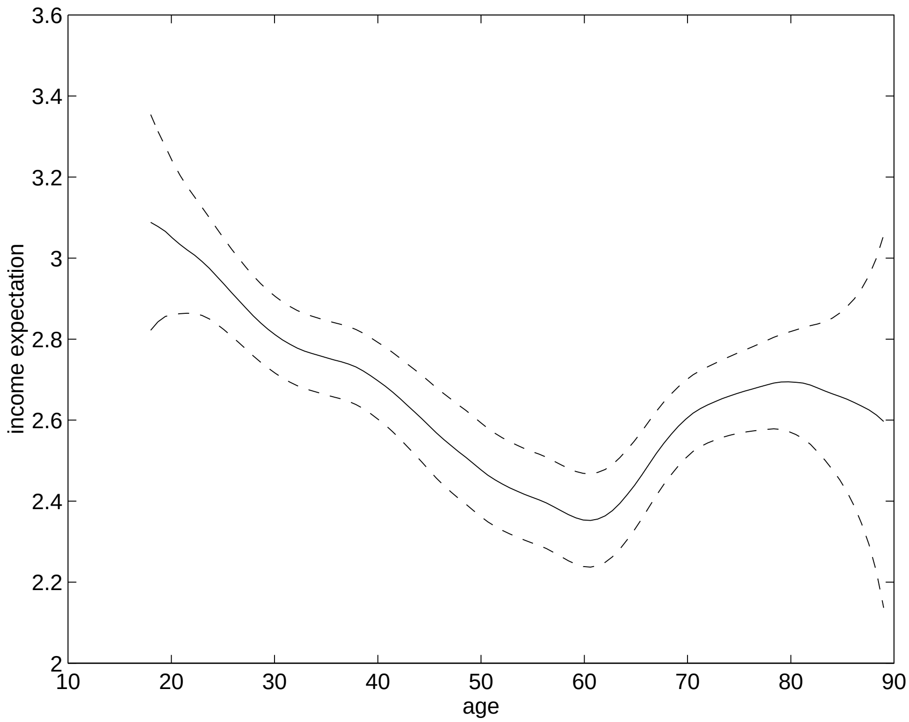


Figure 2.1 displays the nonparametric regression of income expectation on age. We see that heads of households, on average, more often expect a fall in income growth when they are older. This pattern changes at the age of (approximately) 60 years. After this age, many people retire and live from some, often predetermined, retirement benefits. This pattern appears to be similar to that of realized income changes: the fraction of people whose actual incomes decline does increase with age, until the age of retirement. This is similar to the U.S. experience.

[6] We used the quartic kernel. For the bandwidth, we used 8.0 in Figure 2.1 and Figure 2.3, and 1.0 in Figure 2.2 and Figure 2.4. For more details on nonparametric regression, see Härdle and Linton (1994).

Figure 2.2 : Nonparametric regression of income expectation (INCEXP) on the logarithm of net income with 95% uniform confidence bounds (dashed lines)

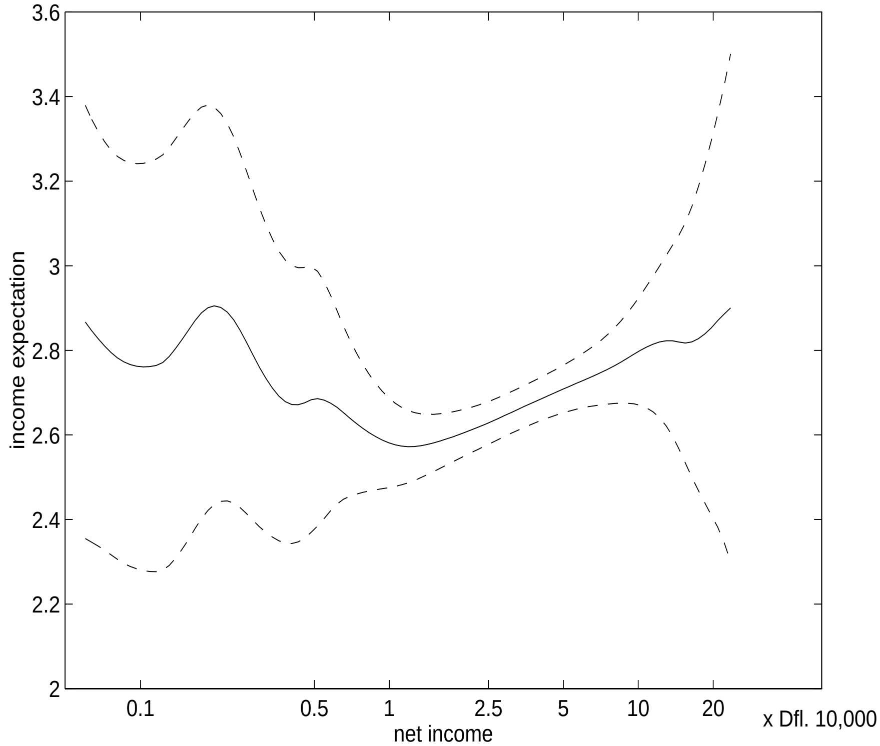


Figure 2.2 plots the nonparametric regression of income expectation on the logarithm of the net income level (for details on the computation of the net income level, see Appendix 2.A). Due to the small number of households receiving a very low income (less than $10,000$ Dutch guilders per year), the first part of the regression line is very inaccurate. [7] For households with an income above $10,000$ Dutch guilders, we see a positive relationship between income expectation and the logarithm of net income: the lower the income, the more often the head of the household expects a fall in family income growth. This corresponds to the increasing inequality of the Dutch income distribution in the time period concerned.[8]

[7] To be precise, 2.6% of the households receive an annual net income less than $10,000$ Dutch guilders.

[8] CBS (1994) reports a slight increase of the Theil coefficient. Income deciles reported by Alessie et al. (1994) reveal a substantial increase of inequality.

2.3 A model for expected income changes

Since INCEXP is a discrete variable with a natural ordering (from 1, strong income decrease expected, to 5, strong increase expected), we model it with an ordered probit model:

$$\begin{aligned} y_i^* &= x_i\beta + \epsilon_i, \\ y_i &= j \text{ if } m_{j-1} \leq y_i^* < m_j \quad (j = 1, ..., 5). \end{aligned} \tag{2.1}$$

Here y_i^* is an unobserved variable, and y_i, INCEXP of family i, is its observed counterpart; x_i is a row vector of family characteristics, including actual income and dummy variables for the possible outcomes of PREV_84, the income change in the past. See Table 2.2 for the included variables and Appendix 2.A and 2.B for definitions and summary statistics of these variables. The random variable ϵ_i is the error term. It is assumed that, conditional upon x_i, it follows a standard normal distribution (with zero mean and unit variance, due to normalization). The bounds satisfy $m_0 = -\infty$, $m_1 = 0$ (by normalization), $m_5 = \infty$; $m_2 < m_3 < m_4$ and β are the parameters to be estimated.

The model is estimated by maximum likelihood. Results are presented in Table 2.2. As expected from Table 2.1, those who experienced a strong income decrease (PREV84_1 = 1) or a decrease (PREV84_2 = 1) in the past twelve months, have significantly [9] less optimistic income change expectations than the reference group of those who have not experienced a change. Those who have experienced a strong fall are more pessimistic than those with a moderate fall. Similarly, those who have experienced an income gain are more optimistic than the reference group. A likelihood ratio test cannot reject the hypothesis that the coefficients on PREV84_4 and PREV84_5 are identical.

Sex of the head of the household appears to play no role. A quadratic age pattern has been included, as suggested by Figure 2.1. INCEXP decreases until about 58 years of age (*ceteris paribus*). This could be a cohort effect as well as a true age effect. The relatively optimistic view of young people could be explained by the fact that earnings increases are usually much larger in the beginning of the working career. For pensioners, income is usually quite stable, which explains the increase for the elderly.

[9] Throughout, we use a (two-sided) significance level of five percent.

Table 2.2 : Parameter estimates for the ordered probit model

DEPENDENT VARIABLE: INCEXP		
Variable	Estimate	T-statistic
INTERCEPT	3.648	14.8
PREV84_1	−0.975	−12.9
PREV84_2	−0.667	−12.2
PREV84_4	0.694	8.55
PREV84_5	0.436	3.37
SEX	0.010	0.12
AGE	−0.622	−6.28
AGE2	0.054	5.30
LOG_INC	3.E-4	0.01
LOG_INC2	0.091	3.77
DSELF	0.421	2.01
DDIR	0.321	1.73
DUNEM	−0.421	−3.85
DRET	−0.123	−1.20
DDIS	−0.607	−6.13
DSOCS	−0.379	−2.27
DOTH	−0.133	−1.38
DSINGLE	−0.037	−0.46
DSINGLEP	0.018	0.17
DTWO	−0.324	−5.26
m_2	1.539	33.1
m_3	3.357	56.3
m_4	4.933	41.1
log-likelihood	−2647.7	

The variables DSELF, ..., DOTH refer to the labor market status of the head of household. The reference group consists of the employees. They are somewhat less optimistic than the self-employed or company directors. Those on unemployment benefits, unemployment assistance, or disability benefits, are significantly more pessimistic about future income changes than employees. In particular, the disabled often expect an income decrease. This can be explained by the fact that the Dutch system of disability benefits went through a substantial reform, which was completed in 1987, but was initiated earlier. In 1985, disability benefits decreased from 80 to 70 percent of the gross wage in the last job. As a result, the after-tax replacement ratio for those on disability benefits decreased from 81.3 percent in 1983 to 78.2 percent in 1984, 72.1 percent in 1985, and 71.3 percent in 1986 [see Aarts and De Jong (1990, p. 39)].

The final three explanatory variables capture family composition and labor market status of the spouse. The reference group consists of one-earner households. Expectations of singles or single parents do not differ significantly from the expectations of one-earner households. Heads of two-earner households, however, significantly more often expect a fall in family income. This may reflect the fact the wife may consider quitting work. A similar effect is found by Dominitz and Manski (1997). We also considered including variables referring to the presence of children in various age groups, but these appeared to have very low significance levels. [10]

In Table 2.3, we present 95% confidence intervals for the probabilities that some reference heads of households expect an income decrease (INCEXP < 3) or an income increase (INCEXP > 3). The first reference case is a male employee, head of a one-earner family, with average age and income level. We look at the impact of the income change in the past twelve months. Second, we consider a disabled head of household.

The effect of PREV_84 appears to be quite strong. Those employed men who have experienced a serious income fall, expect another income fall with probability of at least 60 percent, while their probability of expecting a future income increase is quite small. The reference employees whose incomes have increased, expect a decrease with probability less than 27 percent, and expect an increase with probability at least 10 percent. The disabled heads more often expect an income fall and less often expect an income rise. In most cases, their confidence intervals do not overlap with those of the corresponding employee.

[10] Results of, for example, Kapteyn et al. (1988) suggest that heads of households tend to take little account of the contribution of children's earnings to household income.

Table 2.3 : 95% confidence intervals for the probability of an expected decrease of income and the probability of an expected increase of income as a function of PREV_84

Employed man				
PREV_84	probability of an expected (strong) decrease		probability of an expected (strong) increase	
	lower	upper	lower	upper
1	0.600	0.749	0.006	0.020
2	0.483	0.636	0.015	0.039
3	0.238	0.376	0.064	0.139
4	0.073	0.168	0.189	0.367
5	0.103	0.263	0.115	0.296

Disabled man				
PREV_84	probability of an expected (strong) decrease		probability of an expected (strong) increase	
	lower	upper	lower	upper
1	0.801	0.901	0.001	0.004
2	0.702	0.839	0.002	0.010
3	0.441	0.631	0.015	0.049
4	0.189	0.375	0.064	0.180
5	0.246	0.500	0.033	0.132

Note: confidence intervals are calculated for $P[\,\text{INCEXP} \in \{1,2\} | \,\tilde{x}\,]$ and $P[\,\text{INCEXP} \in \{4,5\} | \,\tilde{x}\,]$ where $\tilde{x}$ is the vector of explanatory variables evaluated at some specific values: the mean of AGE and LOG_INC, DSINGLE = 0, DSINGLEP = 0 and DTWO = 0 (so this implies a head of the household who is a single-earner).

2.4 Link to realized income changes

This section compares the expected income changes to the realized income changes of the same individuals in the same time period. For this purpose, we use the next wave of the SEP (drawn in October 1985). Assuming that no macro-economic shocks have taken place, this comparison gives us an indication to what extent people systematically under- or overestimate their income changes.

Since the SEP is an unbalanced panel, some of the households that were present in the October wave of 1984, are missing in the October wave of 1985. From the 2683 households we used in the previous analysis, 498 households left the panel. Six of the remaining households did not provide information on their realized income changes. This has resulted in a total of 2179 households of which both expected and realized income changes are available. We estimated the ordered probit model in the previous section again, but now with these 2179 households. This yielded almost the same results. That is, the same parameters were significant and all these significant parameters had the same sign. This suggests that the attrition does not lead to serious selectivity problems.

From the October wave of 1985 we take the answer to the question: "Did your household's income increase, decrease, or remain unchanged during the past twelve months?". The answer is denoted by PREV_85, which is comparable with PREV_84. Since we have numerical data on realized income in both 1984 and 1985, we can also calculate the actual income change and compare this with the subjective measure PREV_85. In Table 2.4 the median [11] of the actual change in income between 1984 and 1985 is presented for each outcome of PREV_85. The first column is in nominal terms, while the second column corrects for inflation (2.5%).

Table 2.4 : Median of actual nominal and real income change (in %) for each outcome of PREV_85

PREV_85	nominal change (in %)	real change (in %)
1: strong decrease	-3.49	-5.85
2: decrease	1.18	-1.28
3: no change	3.10	0.59
4: increase	8.54	5.89
5: strong increase	14.9	12.1

The results suggest that respondents base their answers on PREV_85 on real income changes rather than nominal income changes. Moreover, respondents are not symmetric in the sense that an increase in household income has to be larger than a decrease in household income to be considered as *strong* or *moderate* (in absolute value). If respondents provide income change expectations using the same scale, these results can also be used to interpret the values of INCEXP.

As before, we can look at a bivariate frequency table to get some first information on the relationship between expected income changes (INCEXP) and realized income

[11] We use the median instead of the mean because the median is less sensitive for some outliers.

changes (PREV_85). This is done in Table 2.5. About 23.2% of the households experienced a decrease in household income, while the income of 20.3% of the households increased. When we compare the (univariate) frequencies of PREV_85 (Table 2.5) with those of PREV_84 (Table 2.1), we see a shift to the right. This means that, on average, PREV_85 is higher than PREV_84. For 49.6% of the households the expected and realized income changes are the same. Most of them neither expected nor experienced an income change. The dispersion in expected income changes is (again) much smaller than in realized income changes (see also Table 2.1).

Table 2.5 : Bivariate frequencies (in %) of INCEXP and PREV_85

PREV_85 → INCEXP ↓	1	2	3	4	5	total
strong decrease: 1	1.8	1.3	1.9	0.6	0.1	5.7
decrease: 2	3.5	8.3	16.8	3.2	0.6	32.4
no change: 3	1.7	5.5	34.2	7.3	1.6	50.2
increase: 4	0.4	0.8	3.5	5.0	1.5	11.2
strong increase: 5	0.0	0.0	0.1	0.0	0.3	0.5
total	7.3	15.9	56.5	16.2	4.1	100.0

It seems reasonable to assume that the head of household has the same concepts in mind while answering questions on INCEXP and PREV_85. Therefore, if the value of INCEXP is greater than the corresponding value of PREV_85, then the head of household has overestimated future household income growth. Analogously, if the value of INCEXP is smaller than PREV_85, then income growth has been underestimated. From Table 2.5, it follows that 15.5% of the households overestimated their future income growth. On the other hand, 34.9% of the households underestimated their future income growth. From this, it is obvious that, on average, people significantly underestimate their income growth. [12]

[12] This is confirmed by a simple conditional sign test. Out of the 1096 observations with some deviation between expected and actual change, only 336 overestimated their future income change. This leads to a value of the test statistic of -12.8, exceeding the 97.5 percent critical value of the standard normal.

It would be interesting to know what can explain, and to what extent, the fact that, on average, people underestimate their income growth. For this purpose we construct the variable DEV, which denotes the deviation between realized and expected income change: PREV_85 − INCEXP. Note that this variable can in principle vary from −4 to 4. However, as can be seen from Table 2.5, no observations are in the category corresponding to −4. Therefore, DEV only takes the values −3 to 4. A negative value of DEV corresponds with overestimation and a positive value corresponds with underestimation.

To see how the age of the head of household or the logarithm of net household income influence DEV, we regress DEV (nonparametrically) on these two variables. The results are displayed in Figures 2.3 and 2.4.

Figure 2.3 : Nonparametric regression of the difference between PREV_85 and INCEXP on age with 95% uniform confidence bounds (dashed lines)

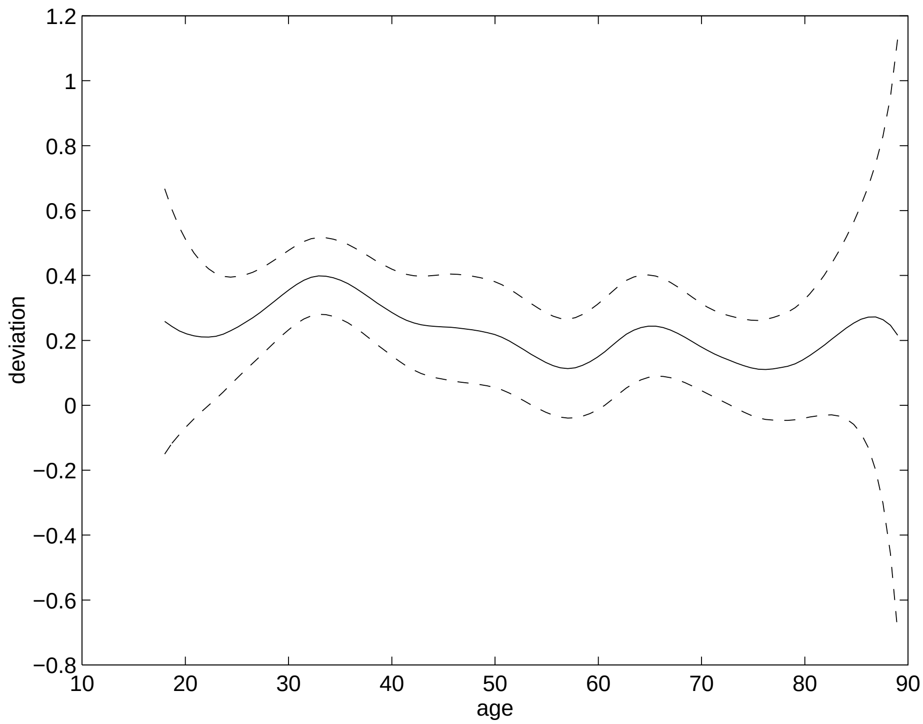
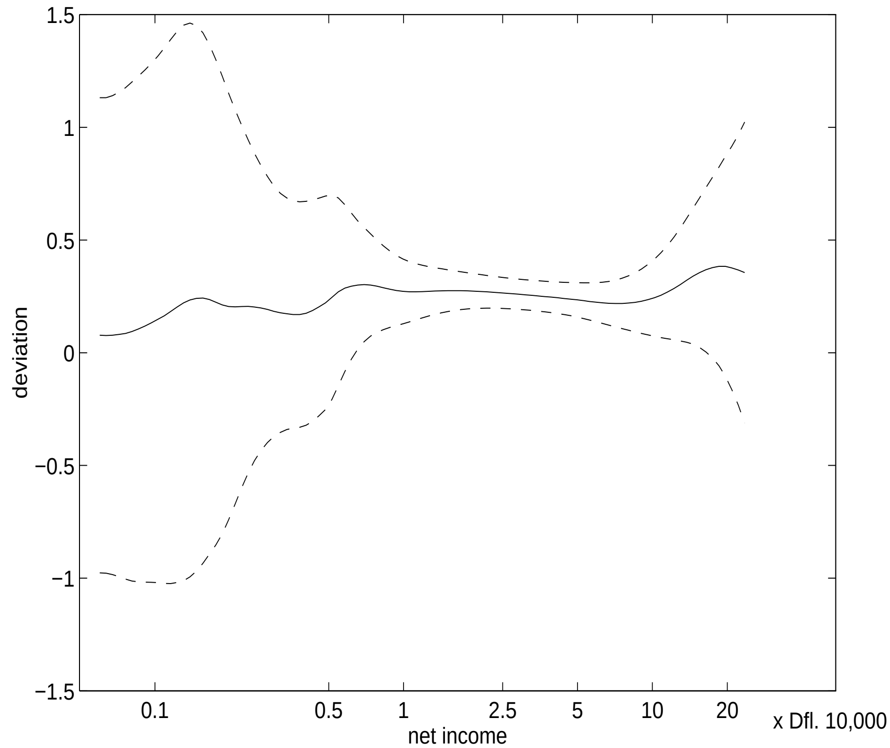


Figure 2.4 : Nonparametric regression of the difference between PREV_85 and INCEXP on the logarithm of net income with 95% uniform confidence bounds (dashed lines)



In both figures we see hardly any evidence that age or net household income can explain the difference between realized and expected income change. This implies that the decreasing income change expectations with age and income in Figures 2.1 and 2.2 correspond to a similar decreasing pattern with age and income in actual income changes. The two compensate each other, leading to the flat patterns in Figures 2.3 and 2.4. We decided to maintain the quadratic specification that we used in the ordered probit model of Section 2.3 in the model that explains DEV.

To explain DEV, consider an ordered response model [see equation (2.1)] with the same explanatory variables as in Section 2.3 (Table 2.2). The results are presented in Table 2.6.

We see in Table 2.6 that most of the parameters corresponding to the explanatory variables are insignificantly different from 0. The most important factor is the income change in the past (reported in October 1984, PREV_84). Especially when income has fallen in the past, people tend to underestimate their future income growth. Compared to those who have experienced no income change in the past, those whose incomes have increased in the past have a smaller tendency to underestimate future income growth. The difference is significant for those who experienced a small increase, but not for those who experienced a large increase.

Table 2.6 : Parameter estimates for the ordered probit model

DEPENDENT VARIABLE: DEV		
Variable	Estimate	T-statistic
INTERCEPT	3.008	10.6
PREV84_1	0.368	4.61
PREV84_2	0.261	4.55
PREV84_4	-0.178	-2.12
PREV84_5	-0.044	-0.33
SEX	-0.116	-1.20
AGE	-0.033	-0.31
AGE2	-0.004	-0.32
LOG_INC	-0.021	-0.33
LOG_INC2	-0.003	-0.11
DSELF	-0.357	-1.61
DDIR	0.039	0.19
DUNEM	-0.035	-0.30
DRET	0.036	0.32
DDIS	-0.288	-2.71
DSOCS	0.010	0.05
DOTH	0.048	0.46
DSINGLE	0.081	0.95
DSINGLEP	-0.182	-1.59
DTWO	-0.076	-1.18
m_2	0.757	7.13
m_3	1.633	14.4
m_4	3.060	26.5
m_5	4.109	34.3
m_6	4.956	36.5
m_7	5.861	24.4
log-likelihood	-2832.5	

Compared to employees, disabled persons appear to have less tendency to underestimate their future income changes. The explanation could be that some of the disabled did not anticipate the reduction of disability benefits in 1985 (see previous section), even though, according to the results in Section 2.3, many people did.

As in Section 2.3 we present 95% confidence intervals for the probabilities that some reference heads of households overestimate (DEV < 0) or underestimate (DEV > 0) their future income growth for different values of the income change in the past twelve months (PREV_84). These confidence intervals are displayed in Table 2.7.

Table 2.7 : 95% confidence intervals for the probability of overestimating and the probability of underestimating future income changes as a function of PREV_84

Employed man					
PREV_84	Prob. of overestimating future income = P_o		Prob. of underestimating future income = P_u		T-value
	lower	upper	lower	upper	
1	0.033	0.183	0.298	0.664	2.94
2	0.042	0.210	0.266	0.619	2.47
3	0.073	0.290	0.190	0.515	1.28
4	0.097	0.361	0.141	0.451	0.47
5	0.070	0.329	0.161	0.523	0.94

Disabled man					
PREV_84	Prob. of overestimating future income = P_o		Prob. of underestimating future income = P_u		T-value
	lower	upper	lower	upper	
1	0.059	0.273	0.204	0.558	1.54
2	0.072	0.311	0.174	0.516	1.08
3	0.115	0.408	0.116	0.413	0.02
4	0.149	0.485	0.082	0.352	0.68
5	0.111	0.449	0.096	0.419	0.14

See also note Table 2.3. The T-value represents the absolute value of the T-statistic for the null-hypothesis that the probability of overestimating equals the probability of underestimating, that is $P_o = P_u$. The distribution under the null is calculated with the use of the delta method.

We see in Table 2.7 that especially for those whose incomes have fallen in the past, the probability of underestimating future income growth is quite high. Given a past (strong) decrease in income for the employed man, the probability of underestimating is significantly higher than the probability of overestimating future income growth. In the case of a past (strong) increase in income, the null-hypothesis $P_o = P_u$ cannot be rejected. For the disabled men, we cannot conclude that they have a higher probability of underestimating future income growth. When we compare the confidence intervals for a disabled male head of household with those of the employed male head, we see that the intervals for the probability of overestimating future income growth are slightly shifted to the right and the intervals for the probability of underestimating future income growth are slightly shifted to the left. The intervals overlap, however, to a large extent.

Macro-economic shocks and rational expectations

The common approach in the majority of empirical studies on life cycle models for household behavior is to assume that the distribution of actual income changes and the distribution of expected income changes coincide. Our data show that this assumption is not realistic. Various explanations for this are possible. The first is an unanticipated positive macro-economic shock that may have taken place in 1985. This is in line with predictions and realizations of unemployment. In 1984, the Netherlands Bureau for Economic Policy Analysis (CPB) expected unemployment to change from $820,000$ in 1984 to $830,000$ in 1985. In reality, however, unemployment fell in 1985 to $760,000$ [see CPB (1986, Table IV.1) and CPB (1984, p. 22)]. Under- or overestimation of disposable income level for employees is less unambiguous. Both in nominal and in real terms, the predicted wage increase is close to the realized increase [see CPB (1984, Table IV.6) and CPB (1985, Table III.4)].

This suggests that at least part of the underestimation could be explained by a macro shock. On the other hand, it then seems hard to understand why there are substantial differences between various groups. In particular, a macro shock cannot explain our finding that those who have experienced an income decrease in the past, underestimate their future income growth much more often than others: we cannot think of a good reason why the impact of macro-economic shocks would be correlated with the income change in the past (conditional on other characteristics, such as actual income, age, and employment status). The finding that the deviation between expected and actual income change in 1985 depends on the actual income change in 1984, is also confirmed by a likelihood ratio test, obtained by comparing our model with a restricted ordered probit model in which PREV84_1, ..., PREV84_5 are excluded. (The value of the test statistic was 44.2, exceeding $\chi^2_{4;0.05} = 9.49$.)

A second explanation is that some groups of people are simply too pessimistic, on average. This means that the rational expectations hypothesis is rejected. [13] This could be an additional explanation why people save more than the standard life cycle model predicts. It seems related to the well-known precautionary savings motive [cf. Kimball (1990)], but it is different: according to the precautionary savings motive, people have rational expectations, but are prudent. As a consequence, they save extra if their income uncertainty is high. Our findings seem to suggest that particularly those who experienced an income decrease in the past, have future expectations that are too pessimistic.

To check the robustness of this result, we estimated the same model for deviations between expectations and realizations, but then using the panel waves of 1985 and 1986. Compared to Table 2.5, the pattern for these years is similar, but less extreme: 15.7% overestimated and 28.9% underestimated their 1986 income change (again, a significant difference). The main finding is that, as in Table 2.6, the impact of the dummy variables indicating that the household experienced a decrease in the past, is significantly positive. This is at odds with the rational expectations hypothesis. Although macro-economic shocks could explain why people on average underestimate future income growth, they cannot explain why those whose income has decreased more often underestimate than others.

2.5 Conclusions

We have analyzed information on future income expectations of Dutch households. We used data on more than $2,000$ households in the SEP, with information on realized income change in 1984, expected income change in 1985, [14] and, from the next panel wave, realized income in 1985. We have started with an analysis of the discrete variable concerning expected income changes. Our first finding is that about half of the population does not expect any change. This implies that the current income level is a dominant predictor of the future income level, a result earlier found by Dominitz and Manski (1997). Second, we find that many more people expect an income decrease than an income increase. To a large extent, this can be explained from the past: the realized income change in 1984 appears to have a very strong impact on the expected

[13]Using completely different data and methods, Hey (1994) also finds evidence against the rational expectations hypothesis.

[14]To be precise, 1984 (1985) here means from October 1983 (1984) to October 1984 (1985) (the time of the interview).

income change in 1985, although large expected changes are rare, even for those who experienced large changes in the past. Third, we find a positive correlation between the actual income level and the expected income change. The rich more often expect to get richer, the poor more often expect to get poorer. The tendency to expect an income fall tends to increase with age, until close to retirement. Finally, labor market status of the head of household and spouse are also significant. For example, disabled heads more often expect an income fall than others, anticipating the reform of the disability benefits system, which was initiated in 1985.

In the second part of the chapter, we compare realized income changes for 1985 with expected income changes for 1985. We first find that realizations are substantially better than expectations, on average. Secondly, we focus on the deviation between realization and expectation and find that particularly those who experienced an income loss in 1984 tend to underestimate their income growth in 1985. The first result may well be explained from an unanticipated macro-economic shock in 1985. The second result, however, is hard to explain by a macro-economic shock and could be interpreted as evidence against the rational expectations hypothesis. This same result is also found when comparing expectations for 1986 reported in 1985 with realizations in 1986.

Whether this explanation is indeed correct, should be further investigated by considering more years. If systematic deviations between expectations and realizations are persistent over a long period of time, macro-economic shocks can be excluded, and rational expectations would be rejected. In the next chapter we focus on six rather than two waves of the SEP. We estimate a panel data model and analyze the robustness of the results found in this chapter.

2.A Appendix: reference list variables

INCEXP Answer to the question : "What will happen to your household's income in the next twelve months ?" Possible answers are: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).

PREV_84 Answer to the question : "Did your household's income increase, decrease, or remain unchanged during the past twelve months ?" Possible answers: see INCEXP.
This variable is in the analysis also represented as dummy-variables: PREV84_$i = 1$ if PREV_84 $= i$; 0 otherwise ($i = 1, \ldots, 5$).

SEX Sex head of household: 1 = male; 2 = female.

AGE Age head of household in tens of years.

LOG_INC Natural logarithm of net household income where net household income is in tens of thousands (per year). The survey contains accurate information on income from about twenty potential sources for each individual. After-tax household income was constructed by adding up all income components of all family members and some specific household components.

Dummy-variables corresponding to social economic category:

DSELF 1 if head of household is self-employed; 0 otherwise.

DDIR 1 if head of household is director of ^{A}Inc. or ^{B}Ltd; 0 otherwise.

DEMP 1 if head of household is employed; 0 otherwise.

DUNEM 1 if head of household is unemployed; 0 otherwise.

DRET 1 if head of household is retired; 0 otherwise.

DDIS 1 if head of household is disabled; 0 otherwise.

DSOCS 1 if head of household is person on social security; 0 otherwise.

DOTH 1 corresponds with other persons than above mentioned without profession; 0 otherwise.
Note: DSELF $+ \ldots +$ DOTH $= 1$.

Dummy-variables corresponding to family composition and labor market status of spouse:

DSINGLE 1 if head of household is single; 0 otherwise.

DSINGLEP 1 if head of household is single parent; 0 otherwise.

DONE 1 if household is a single-earner household; 0 otherwise.

DTWO 1 if household is a two-earner household; 0 otherwise.
Note: DSINGLE $+ \ldots +$ DTWO $= 1$.

2.B Appendix: summary statistics

Variable	Nr. Obs.	Mean	Std. Dev.	Min.	Max.
INCEXP	2683	2.66	0.76	1	5
PREV_84	2683	2.67	0.90	1	5
PREV_85	2179	2.93	0.88	1	5
SEX	2683	1.20		1	2
Age head of household	2683	46.6	17.0	18	89
Net household income	2683	34834	19845	600	235134
DSELF	2683	0.012			
DDIR	2683	0.015			
DEMP	2683	0.554			
DUNEM	2683	0.045			
DRET	2683	0.158			
DDIS	2683	0.068			
DSOCS	2683	0.024			
DOTH	2683	0.124			
DSINGLE	2683	0.227			
DSINGLEP	2683	0.079			
DONE	2683	0.490			
DTWO	2683	0.204			

Chapter 3

A Panel Data Model for Subjective Information

Subjective expectations about future income changes are analyzed, using household panel data. The models used are extensions of existing binary choice panel data models to the case of ordered response. We consider both random and fixed individual effects. The random effects model is estimated by maximum likelihood. The fixed effects model is estimated by combining conditional fixed effects logit estimates using minimum distance. We find that income change expectations strongly depend on realized income changes in the past: those whose incomes fell are more pessimistic than others, while those whose incomes rose are more optimistic. Expected income changes are also significantly affected by employment status and family composition. Using the same type of models, subjective expectations are then confronted with the head of household's ex post perception of the realized income change for the same period. The main finding is that households whose incomes have decreased in the past underestimate their future income growth.

3.1 Introduction

Chapter 2 explains expected income changes from previous income changes and analyzes differences between income expectations and realizations over the same time period. We find that many people underestimate their future income growth, particularly those whose incomes have fallen in the past. While Chapter 2 focuses on one panel wave, this chapter uses an unbalanced panel of Dutch households for the period

1984 – 1989. We can thus analyze the robustness of the results over time. This is particularly important due to the potential presence of macro-economic shocks, which may imply that results are time specific. Moreover, it allows for the incorporation of fixed household specific effects. To our knowledge, this is the only survey in which information on income expectations for the same households are available for a number of consecutive years. We focus on income expectations and realizations and use the same survey questions on actual and expected income changes as in Chapter 2, drawn from the Dutch Socio-Economic Panel (SEP).

The survey questions refer to categories and do not provide information on exact realized or expected income changes. Our dependent variables are therefore of an ordered discrete nature. Although the literature on panel data has expanded rapidly, economic applications of panel data models for discrete data are rather scarce. Examples can be found in Chamberlain (1984) and Pfeiffer and Pohlmeier (1992). [1] Most applications for discrete data consider a binary response. We extend the binary response model to the case of ordered response.

We consider both random and fixed individual effects. The extension in the random effects case is straightforward. In the fixed effects case, we use the conditional logit approach by Chamberlain (1980) after aggregating adjacent categories to two categories. The final estimate for the ordered response model is then obtained by combining the estimates for separate combinations of categories with a minimum distance procedure.

We basically aim at answering the following questions: *Is the use of our type of subjective data feasible and is it useful?* The first question boils down to asking: *do the answers make sense?* We claim that they do, by describing them for the six years and by showing that their relation to various background variables is rather robust over time and of the expected sign. The second question can be restated as follows: *are the subjective data in conflict with the usual assumptions on rational expectations and (absence of) macro-economic shocks?* Our analysis of the deviations between expectations and realizations suggests that they are, and that the assumptions on rational expectations or absence of macro-economic shocks are not valid. This makes it worthwhile to replace these assumptions by information based upon the subjective information in the data.

The organization of this chapter is as follows. Section 3.2 formulates the panel

[1] More applications exist in the fields of biology, psychology and biomedicine. An example of the latter is Gibbons et al. (1994).

data model for the ordered responses. Section 3.3 uses this model to explain income change expectations. Among the explanatory variables are the actual income level and information on the realized income change during the previous year. To see whether groups with different labor market status have (ceteris paribus) different income expectations, we also include dummy variables for being unemployed, disabled, or retired. Section 3.4 first examines subjective information on realized income changes and shows that it relates quite well to more traditional measures of income change, at least on average. We then use the same type of econometric model to compare the expectations in year t with the realizations in year $t+1$ ($t = 1984, \ldots, 1988$). The dependent variable is then based upon the difference between the answers to the questions on expected and realized income changes. Section 3.5 summarizes our findings.

3.2 Panel data models for ordered categorical data

Our starting point is the well-known binary choice panel data model with time varying parameters and individual effects:

$$\begin{aligned} y_{i,t}^* &= \beta_t' x_{i,t} + \alpha_i + u_{i,t}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \\ y_{i,t} &= 1(y_{i,t}^* \geq 0) \end{aligned} \tag{3.1}$$

in which $\beta_t \in \mathbb{R}^k$ and $1(A)$ is the indicator function which is equal to 1 if A is true and 0 otherwise. The index i represents the household and index t represents time. Instead of observing $(y_{i,t}^*, x_{i,t}')'$, one observes $(y_{i,t}, x_{i,t}')'$, in which $x_{i,t}$ is a k-dimensional vector of explanatory variables, including a constant term.

We assume that x_i and u_i are independent, where $x_i = [x_{i,1}', x_{i,2}', \ldots, x_{i,T}']'$ and $u_i = [u_{i,1}, u_{i,2}, \ldots, u_{i,T}]'$. The mutually independent disturbances $u_{i,t}$ are assumed to follow some distribution with mean 0 and variance σ^2. We consider the normal and the logistic distribution.

It is straightforward to extend model (3.1) to allow for more than two outcomes for $y_{i,t}$. Suppose $y_{i,t}$ can take p possible outcomes. As in model (3.1), these outcomes are assumed to be determined by an underlying latent variable $y_{i,t}^*$. The relation between $y_{i,t}$ and the underlying latent variable is modelled by

$$\begin{aligned} y_{i,t}^* &= \beta_t' x_{i,t} + \alpha_i + u_{i,t}, & i = 1, \ldots, N, \quad t = 1, \ldots, T \\ y_{i,t} &= j \quad \text{if } m_{j-1} < y_{i,t}^* \leq m_j & j = 1, \ldots, p \end{aligned} \tag{3.2}$$

where $m_0 = -\infty$ and $m_p = \infty$. To identify the model, we have to fix the location and scale.

For the individual effect α_i we will discuss two specifications. Section 3.2.1 assumes a random individual effect and Section 3.2.2 treats the individual effect as fixed.

3.2.1 Random effects specification

The random effects model consists of model (3.2) together with additional assumptions on the *random* individual effect α_i. We assume that α_i is normally distributed with mean 0 and variance σ_α^2. [2] Moreover, we assume that x_i, u_i, and α_i are independent.

In general, the likelihood function for model (3.2) is a T-variate integral. However, under the assumption of independence made above, the multivariate integral can be reduced to a single integral by integrating out the individual effect. The integrand is then a product of one normal density and T differences of values of the distribution function F_σ of $u_{i,t}$, with σ as a scale parameter (see Butler and Moffitt, 1982). The contribution $\text{Prob}(y_{i,1}, \ldots, y_{i,T})$ for individual i to the likelihood function is given by

$$\int_{-\infty}^{\infty} g(\alpha_i)[\prod_{t=1}^{T}\{F_\sigma(m_{y_{i,t}} - \beta_t' x_{i,t} - \alpha_i) - F_\sigma(m_{y_{i,t}-1} - \beta_t' x_{i,t} - \alpha_i)\}]\mathrm{d}\alpha_i, \tag{3.3}$$

where $g(\alpha_i)$ is the density of $N(0, \sigma_\alpha^2)$. The boundaries $m_j (j = 1, \ldots, p-1)$ are assumed to be constant across individuals.

The model described so far is only applicable for balanced panels. Since the data set we use in our analysis is unbalanced, the notation should be slightly adapted. Define

$$c_{i,t} = \begin{cases} 1 & \text{if individual } i \text{ is in wave } t, \\ 0 & \text{otherwise.} \end{cases} \tag{3.4}$$

We assume that $c_{i,t}$ is independent of $u_{i,t}$ and α_i, implying that we do not allow for selection or attrition bias. The likelihood contribution for individual i is then given by [cf. (3.3)]

$$\int_{-\infty}^{\infty} g(\alpha_i)[\prod_{t=1}^{T}\{F_\sigma(m_{y_{i,t}} - \beta_t' x_{i,t} - \alpha_i) - F_\sigma(m_{y_{i,t}-1} - \beta_t' x_{i,t} - \alpha_i)\}^{c_{i,t}}]\mathrm{d}\alpha_i.$$

[2] For random effects models in which the assumed family of distributions for the individual effect adopts a variety of forms and shapes, see Crouchley (1995).

3.2.2 Fixed effects specification

One major limitation of the random effects specification is the assumption that the individual effect α_i is uncorrelated with the $x_{i,t}$. This can be relaxed by treating α_i as a fixed effect – implying that each α_i becomes an unknown parameter. In the fixed effects specification, the levels of the slope coefficients $\beta_{t,k}$ are only identified if the corresponding regressors $x_{i,t,k}$ vary over time. For time-invariant $x_{i,t,k}$, only the differences $\beta_{t,k} - \beta_{s,k}$ are identified, implying that without loss of generality, the coefficients of one time period can be normalized to zero.

In this fixed effects model, the number of parameters increases with the number of individuals N. ML estimates of the α_i and the $\beta_{t,k}$ will be inconsistent if N becomes large but T is finite. This is known as the incidental parameter problem (Neyman and Scott, 1948). For the binary choice panel data model, Chamberlain (1980) suggested an approach based upon a conditional likelihood function to estimate the $\beta_{t,k}$. The key idea is to work with a conditional likelihood function, conditioning on sufficient statistics for the nuisance parameters α_i. This idea works if the disturbance terms $u_{i,t}$ are i.i.d. and follow a logistic distribution. In that case the minimum sufficient statistic for α_i is $\sum_{t=1}^{T} y_{i,t}$. Given this statistic, the contribution of individual i to the conditional likelihood function is, in case of a balanced panel

$$\text{Prob}(y_{i,1}, \ldots, y_{i,T} | \sum_{t=1}^{T} y_{i,t}) = \frac{\exp[\sum_{t=1}^{T}(x'_{i,t}\beta_t) y_{i,t}]}{\sum_{d \in B_i} \exp[\sum_{t=1}^{T}(x'_{i,t}\beta_t) d_t]}, \tag{3.5}$$

where

$$B_i = \{d = (d_1, \ldots, d_T) \mid d_t = 0 \text{ or } 1, \text{ and } \sum_t d_t = \sum_t y_{i,t}\}.$$

It does not depend on the incidental parameters α_i and the conditional ML estimator of β_t is, under mild regularity conditions, consistent and asymptotically normal.

A direct extension of this approach to an ordered response panel data model where the dependent variable has $p > 2$ possible outcomes, is not straightforward and even seems impossible. However, we can combine adjacent categories so that the dependent variable is summarized as a binary variable, and then use the conditional logit method. If we repeat this for all the possible combinations of adjacent categories, we get $p - 1$ estimates of the parameters of interest. [3] These estimates can then be combined

[3] The boundaries m_j are not estimated and can be seen as nuisance parameters. Moreover, in the fixed effect specification the boundaries are allowed to depend on i.

into one final estimate of the parameters of interest by using minimum distance. See Appendix 3.A for some details.

It is straightforward to extend this estimation procedure to the case of an unbalanced panel. Again, the notation should slightly be adapted. We define $c_{i,t}$ as in (3.4) and assume that $c_{i,t}$ and $u_{i,t}$ are independent to exclude attrition and selectivity bias. Then the conditional probability for the binary case [cf. (3.5)] is given by

$$\text{Prob}(y_i|\sum_{t=1}^{T} c_{i,t}y_{i,t}) = \frac{\exp[\sum_{t=1}^{T} c_{i,t}(x'_{i,t}\beta_t)y_{i,t}]}{\sum_{d\in\tilde{B}_i} \exp[\sum_{t=1}^{T} c_{i,t}(x'_{i,t}\beta_t)d_t]},$$

where y_i is the vector with observed $y_{i,t}$ and $\tilde{B}_i$ is analogous to B_i for relevant vectors d ($\forall c_{i,t} = 0 : d_t = 0$). The unbalanced nature of our data is also the reason why we do not consider quasi fixed effects models (see Chamberlain, 1984) in which α_i is allowed to be correlated with the $x_{i,t}$. The fact that $x_{i,t}$ is unobserved in some waves would then lead to ad hoc adjustments of the correlation pattern (or to joint modelling of the $x_{i,t}$ with the $y_{i,t}$ and the specification and computational problems involved with that).

3.3 Data and estimation results

Data are taken from the Dutch Socio-Economic Panel (SEP) Households were interviewed in October 1984 and then twice a year (April and October) until 1989. Since 1990, the survey has been conducted only once a year in May. In the October interview, information about income is gathered. We focus on the waves of 1984 through 1989, because in 1990 the questions related to (actual) income changed substantially.

The attrition rate in the panel is about 25 percent on average, and tends to decrease over time. New households have entered the panel each year. After eliminating observations with item nonresponse, mainly due to missing information on one or more components of actual household income, we retained a sample of 6845 households. Only 722 of them are in the balanced subpanel (10.5%). This is the reason why we do not estimate the model for the balanced subpanel only, but focus on the unbalanced panel. For 14% of all households, the required information is available in five waves, for 18% in four, for 16.8% in three, and for 16.4% in two waves. The remaining households (24.3%) provided information for only one wave. Most of those who are in more than one wave participate in consecutive waves. In the final data set used for estimation, about 24% are included in non-consecutive waves, mainly due to item nonresponse. The numbers of observations per wave are included in Table 3.1.

Heads of households are asked to answer the question

> *What will happen to your household's income in the next twelve months? Possible answers: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).*

The distribution of the answers, which will be denoted by EXP_t ($t = 84, \ldots, 89$), are given in Table 3.1. We see that except for 1984 the number of households expecting a strong decrease is relatively low. If we aggregate the categories *strong decrease* and *decrease*, we see that (with the exception of 1987) the number of households expecting a fall in household income decreases.

Table 3.1 : Univariate frequencies (in %) of EXP_t ($t = 84, \ldots, 89$)

EXP_t	84	85	86	87	88	89
# observations	2683	2787	3850	3899	4059	4133
1: strong decrease	5.9	1.9	1.6	2.3	1.3	1.3
2: decrease	33.1	18.9	12.6	15.8	10.9	8.2
3: no change	50.3	62.4	66.4	63.9	68.6	63.2
4: increase	10.3	16.0	18.6	17.4	18.4	26.5
5: strong increase	0.4	0.9	0.8	0.6	0.9	0.9

Since the number of answers in the categories *strong decrease* and *strong increase* is quite low, we decided to combine categories 1 and 2 and categories 4 and 5. This means that we have three possible outcomes for the dependent variable EXP_t: p equals 3 in equation (3.2). The explanatory variables in the equation for the underlying unobserved variable include (dummies for) income changes in the past, sex, age, actual income, and dummy variables for the labor market status of the head of household and spouse. We refer to Appendix 3.B for definitions of these variables and to Appendix 3.C for some descriptive statistics.

First we estimate the ordered *random effects* model described in Section 3.2.1. We fix $m_1 = -1$ by means of normalization. The random effects α_i are assumed to be normally distributed. For the distribution of the error terms $u_{i,t}$, we chose the (standard) logistic distribution. We also estimated the random effects model with a normally distributed $u_{i,t}$. The results were almost the same. That is, the same parameters were significant and all these significant parameters had the same sign. Vuong's (1989) model selection test, however, suggests that the model with logistic $u_{i,t}$ fits the data significantly better than the model with normally distributed $u_{i,t}$. [4]

The total number of observations in the pooled sample is equal to 6845. Table 3.2a presents the estimation results. No restrictions are imposed upon the slope coefficients across the various waves. The estimates here are very similar to the estimates obtained when estimating the cross-section model for each separate wave. The only joint elements are the boundary m_2, and the variance of the random effect, which picks up about 20% of the total error variance (σ_u^2, the variance of the standard logistic distribution, is equal to $\pi^2/3$). Joint estimation has the advantage that stability of coefficients over time can be tested straightforwardly. The final column of Table 3.2a presents the test results.[5]

Table 3.2a : Estimation results for the ordered random effects model

DEPENDENT VARIABLE: EXP_t ($t = 84, \ldots, 89$)							
Number of Observations: 6845							
Variable	1984	1985	1986	1987	1988	1989	
CONSTANT	3.91*	4.30*	4.45*	3.81*	4.23*	3.96*	NR
DECR_1	-1.79*	-1.20*	-0.76*	-1.26*	-0.76*	-0.46*	R
INCR_1	1.41*	1.08*	1.14*	0.98*	0.98*	1.04*	NR
SEX	-0.21	-0.10	-0.30*	-0.27*	-0.25*	-0.10	NR
AGE	-1.35*	-0.98*	-0.89*	-0.75*	-0.84*	-0.75*	NR
AGE2	0.12*	0.07*	0.05*	0.04	0.05*	0.05*	NR
LOG_INC	0.30*	0.11	0.09	0.34*	0.26*	0.11	R
DUNEM	-1.00*	-1.27*	-1.03*	-0.68*	-0.73*	-0.04	R
DDIS	-1.65*	-1.30*	-1.04*	-0.98*	-0.92*	-0.05	R
DRET	-0.27	-0.34	-0.07	0.11	-0.02	-0.20	NR
DOTH	-0.07	-0.27*	-0.42*	-0.03	-0.34*	-0.36*	R
DTWO	-0.54*	-0.21	-0.26*	-0.32*	-0.18	-0.27*	NR
σ_α^2	0.75*						
m_2	3.18*						

1) * = significant at 5% level.
2) Null hypothesis: coefficient corresponding to explanatory variable does not vary over time; R = rejected, NR = not rejected (significance level: 5%).

[4] The realization of the test statistic, which should be compared with a critical value of the standard normal distribution, is equal to 14.8.

[5] All tests are Wald tests, based upon imposing $T - 1 = 5$ restrictions in the general model.

The 1984 estimates are similar to those in Chapter 2. Many of these appear to remain stable over time. However, a joint test on the stability of the coefficients AGE and AGE2 rejects the null hypothesis that the age pattern remains constant over time. This suggests that there might be some cohort effect. Households with a female head tend to be less optimistic than other one-earner households: the coefficient of SEX is negative and significant in three of the six years. [6] Except for 1985 and 1988, two-earner households have significantly lower expectations of income changes than other households headed by males.

For none of the years are retired family heads significantly different from working heads. For the dummy variables corresponding to unemployed and disabled family heads, stability over time is rejected. Both reveal a similar tendency: unemployed and disabled heads are significantly more pessimistic than workers (with the same income) in the first five years, but the differences decline and have basically disappeared in the last wave. For the disabled, this may well reflect anticipation of the institutional changes in disability benefit access and levels that started in 1985 and were completed in 1987. For the unemployed, it probably reflects larger expected chances of finding a job due to the upswing of the business cycle.

Those who experienced an income decrease in the past have a larger probability of expecting another income decrease than others (ceteris paribus). This effect is not stable over time and tends to become smaller, but it remains significant throughout the time period under consideration. On the other hand, those who experienced an income increase tend to remain less pessimistic than others, and the difference with those whose incomes did not change during the last twelve months (the reference group) remains stable over time.

Stability over time of the relation between income expectations and the level of actual income LOG_INC (objectively measured) is rejected at the 5% level. Still, the effect is always positive, and significant in three out of the six years. This suggests a tendency of increasing income inequality: the rich relatively more often expect to get richer, the poor expect to get poorer. We come back to this below, where we link this to the findings for the fixed effects model.

In the fixed effects specification, the assumption of independence between the individual effect and the covariates are relaxed (see Section 3.2.2). We normalized the constant term and the coefficients of the variables SEX, AGE, and AGE2, which

[6] For married couples, the head of household is by definition the husband.

do not vary over time or vary over time in a deterministic way, to zero for the first wave. Using Wald tests for each of these variables separately, we found that these variables were insignificant at the 5% level for the other waves. The results we present are those obtained after excluding these variables. Note that with the estimates of the fixed effects specification we do not use data on the households that provided all information in just one wave.

In our application, the number of categories p is equal to 3: decrease ($\text{EXP}_t < 3$), no change ($\text{EXP}_t = 3$), and increase ($\text{EXP}_t > 3$). As mentioned in Section 3.2.2, we summarize the ordered categories into two categories so that we can use the conditional logit procedure. This means that there are two possible summaries: *2* versus *3* and *4*, and *2* together with *3* versus *4*. By using a minimum-distance step, we combine these two estimators to get the final estimates for the β_t's. Table 3.2b shows the final results.

Table 3.2b : Estimation results for the ordered fixed effects model

DEPENDENT VARIABLE: EXP_t ($t = 84, \ldots, 89$)							
Number of Observations: 5185							
Variable	1984	1985	1986	1987	1988	1989	
DECR_1	-1.62*	-0.71*	-0.36*	-0.89*	-0.45*	-0.35*	R
INCR_1	0.60*	0.48*	0.63*	0.31*	0.39*	0.55*	NR
LOG_INC	-0.57*	-0.17*	-0.15*	-0.01	-0.02	-0.04	R
DUNEM	-0.76*	-0.42	-0.58*	-0.30	0.14	0.78*	R
DDIS	-1.66*	-0.74*	-0.55*	-0.73*	-0.33	0.88*	R
DRET	0.22	0.07	0.46*	-2E-3	0.48*	1.13*	R
DOTH	-0.12	-0.06	-0.23*	0.15	-0.06	0.84*	R
DTWO	-0.39*	-0.31*	-0.26*	-0.48*	-0.27	-0.27*	NR

1) * = significant at 5% level.
2) Null hypothesis: coefficient corresponding to explanatory variable does not vary over time; R = rejected, NR = not rejected (significance level: 5%).

For the variables referring to realized income changes in the past, the results are basically the same as those for the random effects model. Those whose incomes decreased in the past are significantly more pessimistic, and those whose incomes increased are more optimistic than those whose incomes remained unchanged. The results for the labor market status variables are also similar to those in Table 3.2a. The only remarkable difference is found for $t = 89$. In Table 3.2a DUNEM, DDIS, and

DRET are not significantly different from zero, while in Table 3.2b all these parameters are significantly positive. This suggests that in 1989 those heads of households who became unemployed, disabled or retired are less pessimistic about future income growth than are the employed heads.

Only for the variable LOG_INC do we find a result that is substantially different from that in the random effects model. The coefficient is negative instead of positive, and significant in three out of the six waves. An explanation is that the fixed individual effect is positively correlated with income. Thus, those with higher 'permanent' incomes are on average more optimistic than others. This is revealed by the positive sign in the random effects model. It suggests that heads of households expect that differentials in incomes per year between those with high and those with low permanent income tend to increase over the life cycle. The estimates of the fixed effects model then tell us that, conditional on the fixed effect and permanent income, those whose incomes are unusually low in a given period often expect an income rise, while those with relatively high income expect their income to fall. This corresponds to the notion that the deviation between actual income and permanent income can be seen as transitory, and that the expected change in transitory income is negatively related to the level of transitory income.

The fixed effects specification is a generalization of the random effects model. The two can be compared using a Hausman test. If the random effects model is correctly specified, the random effects ML estimates for the β_t are consistent and asymptotically efficient. The estimates of the fixed effects model are consistent as long as the fixed effects specification is correct. The Hausman test is based upon the differences of the two sets of parameter estimates. The test leads to a clear rejection of the random effects specification on every sensible significance level.

3.4 Comparing expectations with realizations

Family heads were also asked to answer the question

> *Did your household's income increase, decrease, or remain unchanged during the past twelve months?*

The possible answers, which we denote by PREV_t $(t = 84, \ldots, 89)$, are the same as for EXP_t. Table 3.3 presents the distribution of the answers.

Table 3.3 : Univariate frequencies (in %) of PREV$_t$ ($t = 84, \ldots, 89$)

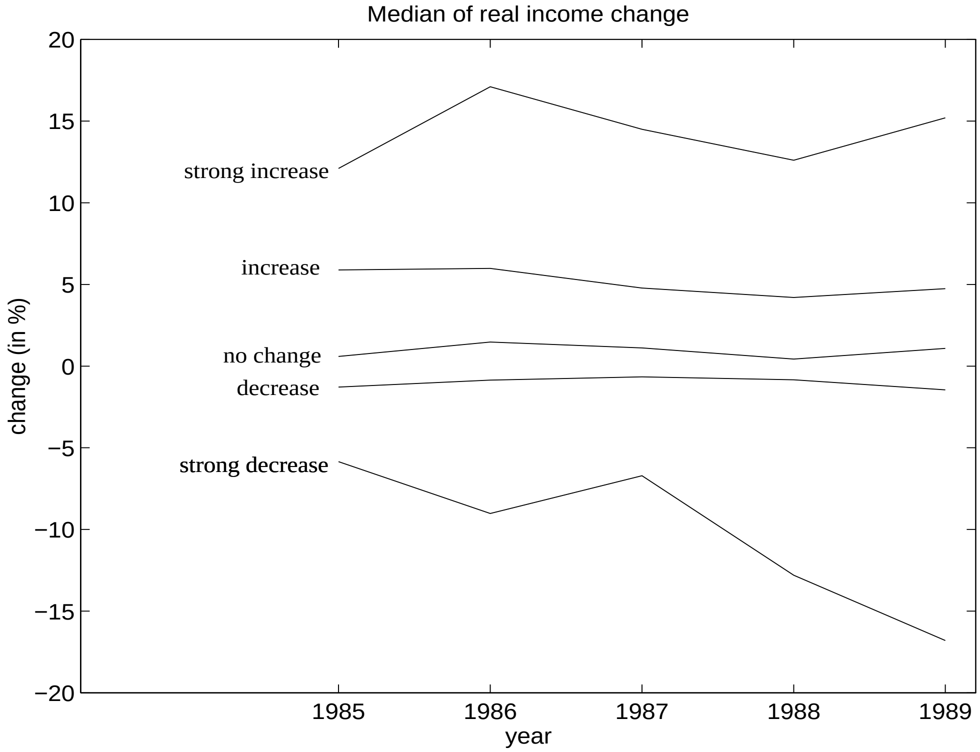
PREV$_t$	84	85	86	87	88	89
1: strong decrease	11.7	9.1	4.9	5.5	4.4	3.8
2: decrease	24.6	16.9	10.7	15.2	9.1	6.9
3: no change	51.6	53.9	56.3	55.8	60.2	56.1
4: increase	9.0	15.7	23.1	19.0	20.4	26.1
5: strong increase	3.1	4.3	5.0	4.5	5.9	7.0

If we compare Table 3.3 with Table 3.1, we see that the dispersion in realized income changes is much larger than in expected income changes. Quite a lot of households experienced a strong decrease or a strong increase. This is not surprising, since the expected income change refers to some location measure of the household's (subjective) income change distribution, while the realization is one draw from the (actual) distribution of income change. The dispersion in the latter is therefore not only due to variation in income growth distributions across families, but also to the uncertainty of the income change for a given household.

Figure 3.1 shows the relation between the answers to the subjective income change question and the objectively measured change in actual real total family income over the same time period (using the consumer price index for each year). We present the median real income change for families with given value of PREV.

The results are quite stable over time, except for those who experienced a large decrease. For those who reported no change (PREV = 3), the median real income change varies between 0.4% and 1.5%. For those who reported an income decrease, the median real change varies from -1.5% to -0.5%; for those who reported an increase, it varies from 4.2% to 6.0%. These numbers are more stable if we consider real rather than nominal income changes. In Chapter 2 we already argued that the subjective answers reflect real rather than nominal changes. Figure 3.1 provides further evidence to support this conclusion. For those reporting a strong increase, the median varies between 12.1% and 17.1%. Only for those who reported a strong decrease, the pattern seems nonstationary, and the median falls from -5.9% to -16.8%. Note, however, that this group has become quite small in 1989 (see Table 3.3).

Figure 3.1 : Relation between the answers to the subjective income change question and the objectively measured change in actual real total family income



Although the questions are not very well specified, it seems reasonable to assume that the head of household has the same concept in mind while answering the questions on PREV_t and EXP_t. Due to the panel nature of the data set, we can compare the expectation of income change (provided in wave t-1) with the realization for the same time period (provided in wave t). If PREV_t is larger than EXP_{t-1}, then we can say that the head of household *ex post* appears to have underestimated household income growth. Analogously, if PREV_t is smaller than EXP_{t-1}, then the income growth is overestimated.

Table 3.4 shows the frequencies of households who under- and overestimated their income changes. In all cases, we see that the percentage of families underestimating exceeds the percentage of families overestimating future income growth. Except for 1986-1987, this difference is highly significant. We find it hard to believe that unanticipated macro-economic shocks explain the fact that this happens several times in a row. Although macro-economic changes may well be correlated over time, we see no reason why the unanticipated element in them should.

Table 3.4 : Frequencies (in %) of under- and overestimating future income changes

	underestimation	overestimation	Test-statistic
1984-1985	34.9	15.4	12.8
1985-1986	29.3	15.9	9.9
1986-1987	22.5	21.5	0.9
1987-1988	29.2	14.6	13.1
1988-1989	28.9	12.5	15.6

Note: A conditional sign test is carried out to test whether the probability of overestimating equals the probability of underestimating future income growth. The third column displays the test-statistic that should be compared with critical values from the standard normal distribution.

A possible weakness of the confrontation of expectations with the realizations given above might be implied by the vague wording of the question. If someone has experienced strong decreases in the past, he may have become used to it, and won't use the word *strong* again (habit formation effect). To eliminate this problem, we recalculated the test-statistics in Table 3.4, but now after combining the categories 1 and 2 and the categories 4 and 5, so that the difference between *strong* and *moderate* is eliminated. The values of the test-statistics for the five years are then given by $14.2, 10.3, 0.1, 12.3,$ and 14.8. Again, the underestimation is significant in four years. Only for 1986-1987 the result is not significant.

Table 3.5 presents the estimates of an ordered response panel data model with fixed effects explaining the deviation $\text{DEVIATION}_t = \text{EXP}_{t-1} - \text{PREV}_t$ between income change expectation and income change realization for the same time period. The model and estimation strategy are those discussed in Section 3.2. The possible values of the dependent variable range from -4 (strong underestimation of future income) to 4 (strong overestimation). This would lead to eight possible conditional logit estimates. However, because of the low numbers of observations in the extreme categories, and for computational convenience, we only use two summaries of the data: $\text{DEVIATION}_t < 0$ versus $\text{DEVIATION}_t \geq 0$ and $\text{DEVIATION}_t \leq 0$ versus $\text{DEVIATION}_t > 0$. The two conditional binary logit estimates are combined using minimum distance.

Again, for each variable, a Wald test is performed on stability over time of the corresponding parameter. Moreover, an additional Wald test is carried out to test whether all parameters corresponding to a specific explanatory variable are equal to zero. Except for the variables LOG_INC, DUNEM, and DTWO, both tests reject the null hypothesis. The unemployed heads do not significantly differ from working heads and heads of two-earner households do not underestimate more or less than other male family heads. Disabled heads have tended to underestimate significantly more than did employed heads in 1988 and 1989. An interpretation of this is that people expected stronger consequences of the reforms of the system of disability benefits.

Table 3.5 : Estimation results for the ordered fixed effects model

DEPENDENT VARIABLE: $\text{DEVIATION}_t = \text{EXP}_{t-1} - \text{PREV}_t$ $(t = 85, \ldots, 89)$							
Number of Observations: 4243							
Variable	1985	1986	1987	1988	1989	$H_0^{(1)}$	$H_0^{(2)}$
DECR_1	-0.60*	-0.97*	-0.78*	-1.16*	-1.09*	R	R
INCR_1	1E-3	0.33*	0.73*	0.87*	0.70*	R	R
LOG_INC	0.18*	0.14	0.06	0.11	0.02	NR	NR
DUNEM	-0.26	0.06	0.32	-0.12	-0.37	NR	NR
DDIS	0.07	-0.20	0.15	-0.70*	-0.82*	R	R
DRET	-0.42	-0.24	0.85*	-0.05	-0.08	R	R
DOTH	-0.49*	-0.08	0.12	-0.03	-0.31*	R	R
DTWO	4E-3	0.34*	0.12	0.03	0.22	NR	NR

1) * = significant at 5%.
2) Hypothesis $H_0^{(1)}$: coefficients corresponding to explanatory variable do not vary over time; Hypothesis $H_0^{(2)}$: all the coefficients corresponding to explanatory variable are equal to 0 (R = rejected, NR = not rejected, significance level = 0.05).

The effects of DECR_1 and INCR_1, the variables indicating an income decrease or increase in the past, are not stable over time. [7] Still, the effect of DECR_1 is significantly negative and the effect of INCR_1 is significantly positive in all years. This implies that those whose incomes have fallen have a larger probability of underestimating than others. This result was also found in Chapter 2. We find that this result is robust over time.

The main findings of this analysis are the following. First, the number of people underestimating future income growth is larger than the number of people overestimating income growth. Second, the tendency to underestimate varies with labor

[7] No account has been taken of potential endogeneity of these variables.

market status and income change history. In particular, those whose incomes have fallen in the past tend to underestimate future income growth. Various explanations could be given for this finding. First, it could be a statistical artifact due to the fact that we are comparing an *ex ante* location measure with an *ex post* realization. Even if households' subjective and actual income change distribution are the same, some heads of households will overestimate and some will underestimate, and, due to the categorical nature of the data, the numbers of those who underestimate and overestimate are not necessarily the same (see Manski, 1990, p. 937, and Chapter 4). Although this might explain why we find an overall tendency of underestimation, we do not think that this argument can explain why particularly those whose incomes fell in the past underestimate.

The second explanation would be the existence of (unexpected) shocks that are correlated across households with certain characteristics. For example, if macro-economic growth rates are larger than expected for various years in a row, this could explain why we find, on average, underestimation. Again, however, it seems hard to imagine that positive shocks are particularly relevant for those whose incomes have fallen in the past.

The third explanation is that people's expectations are not rational, and that households whose incomes have fallen are simply too pessimistic. This could mean that heads of household too often tend to view negative income changes as permanent.

3.5 Conclusions

We have analyzed subjective data on income change expectations and realizations using panel data covering the period 1984 – 1989. Comparing the subjective data with information on actual income suggests that, on average, the data are consistent with the notion that people consider percentage changes in real income. For all panel waves, we find that income growth expectations are strongly affected by previous income changes. The impact of labor market status variables is less stable over time, and this can partly be explained by institutional changes in the time period considered. Comparing random effects and fixed effects estimates of the coefficient of the actual income level leads to the conclusion that those with higher permanent incomes generally have higher expected income growth than others. On the other hand, those with low or negative transitory income often expect an income rise, while those with high transitory income expect their incomes to fall.

Comparing expected and realized income changes for the same time period, we find for all waves (but one) that on average, future income growth was significantly underestimated. In particular, people whose incomes decreased in the recent past tend to be too pessimistic. It seems hard to imagine that this is caused by unanticipated macro-economic shocks. First, we cannot think of shocks that would affect those with a specific income change (and not a specific income level). Second, the effect is remarkably persistent over time. A plausible alternative explanation seems to be that people's expectations are not rational, and that negative transitory incomes are too often considered to be permanent.

Our results thus cast doubt on using the assumption of rational expectations, a common assumption in many empirical studies of life cycle models. Moreover, our results suggest that subjective survey questions contain valuable additional information, which can be used to replace this assumption. Incorporating this in a life cycle model thus seems to be a promising topic of future research.

3.A Appendix: details on estimation procedure

This appendix presents some details on the estimation procedure in the ordered response panel data model with fixed individual effects. For details on the binary case, see Chamberlain (1980).

First we combine adjacent categories so that the dependent variable $y_{i,t}$ is summarized as a binary variable. There are $p-1$ of such combinations and for each combination we use the conditional logit method proposed by Chamberlain (1980). Under some regularity conditions, all the conditional ML estimators for the parameter vector of interest $\beta \in \mathbb{R}^{kT}$ are consistent and asymptotically normal:

$$\sqrt{n}(\hat{\beta}_s - \beta) \to \mathrm{N}(0, (\mathrm{E}\{l_s l_s'\})^{-1}), \qquad s = 1, \ldots, p-1,$$

where l_s is the score vector corresponding to combination s. The fixed effects estimator of β is then obtained by a minimum distance step:

$$\hat{\beta}_{FIX} = \underset{\beta}{\mathrm{argmin}} \frac{1}{2} [\begin{pmatrix} \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_{p-1} \end{pmatrix} - \begin{pmatrix} \beta \\ \vdots \\ \beta \end{pmatrix}]' W^{-1} [\begin{pmatrix} \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_{p-1} \end{pmatrix} - \begin{pmatrix} \beta \\ \vdots \\ \beta \end{pmatrix}].$$

The optimal weighting matrix W is given by $\Omega = [\omega_{a,b}]$ where

$$\omega_{a,b} = (\mathrm{E}\{l_a l_a'\})^{-1} \mathrm{E}\{l_a l_b'\} (\mathrm{E}\{l_b l_b'\})^{-1}, \qquad a, b = 1, \ldots, p-1.$$

In the actual calculations we replace the expectations by their sample analog and the true parameter values by their estimations. Since $\hat{\beta}_{FIX}$ is a linear combination of the consistent estimators $\hat{\beta}_1, \ldots, \hat{\beta}_{p-1}$, the fixed effects estimator is consistent. The asymptotic distribution of the fixed effects estimator is given by

$$\sqrt{n}(\hat{\beta}_{FIX} - \beta) \to \mathrm{N}(0, (D'\Omega^{-1}D)^{-1}),$$

where

$$D = \begin{bmatrix} I_{Tk \times Tk} \\ \vdots \\ I_{Tk \times Tk} \end{bmatrix} \in \mathbb{R}^{(p-1)Tk \times Tk}.$$

3.B Appendix: reference list variables

EXP_t Answer to the question : "What will happen to your household's income in the next twelve months ?" Possible answers are: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5). The subindex t runs from 84 through 89 (where 84 corresponds to the year 1984, etc.).

PREV_t Answer to the question : "Did your household's income increase, decrease, or remain unchanged during the past twelve months ?" Possible answers: see EXP_t.

DECR_1 Dummy variable related to PREV_t: DECR_1 = 1 if PREV_t is equal to 1 or 2; 0 otherwise.

INCR_1 Dummy variable related to PREV_t: INCR_1 = 1 if PREV_t is equal to 4 or 5; 0 otherwise.

SEX Sex head of household: 1 = male; 2 = female. If husband and wife are present, the husband is by definition head of household.

AGE Age head of household in tens of years.

LOG_INC Natural logarithm of net household income where net household income is in tens of thousands (per year). The survey contains accurate information on income from about twenty potential sources for each individual. After-tax household income was constructed by adding up all individual income components of all family members and some specific household components (such as child allowances).

Dummy variables corresponding to labor market status head of household:

DEMP 1 if head of household is employed; 0 otherwise.

DUNEM 1 if head of household is unemployed; 0 otherwise.

DDIS 1 if head of household is disabled; 0 otherwise.

DRET 1 if head of household is retired; 0 otherwise.

DOTH DOTH=1-DEMP-DUNEM-DDIS-DRET.

Dummy variable corresponding to labor market status of spouse:

DTWO 1 if household is a two-earner household; 0 otherwise.

3.C Appendix: summary statistics

Table 3.C.1: Mean values (standard deviations in parentheses)

t	84	85	86	87	88	89
Nr. Obs	2683	2787	3850	3899	4059	4133
EXP_t	2.66	2.95	3.04	2.98	3.07	3.17
	(0.76)	(0.68)	(0.64)	(0.67)	(0.61)	(0.64)
$PREV_t$	2.67	2.89	3.13	3.02	3.14	3.26
	(0.90)	(0.92)	(0.85)	(0.86)	(0.83)	(0.83)
DECR_1	0.36	0.26	0.16	0.21	0.14	0.11
INCR_1	0.12	0.20	0.28	0.24	0.26	0.33
SEX	1.20	1.19	1.19	1.23	1.23	1.23
Age head of household	46.6	46.1	45.6	47.1	47.0	46.9
	(17.0)	(16.4)	(16.2)	(17.0)	(16.9)	(17.0)
Net household income	3.48	3.57	3.64	3.79	3.71	3.79
(in Dfl. 10,000)	(1.98)	(2.24)	(2.12)	(2.98)	(2.32)	(2.21)
DEMP	0.554	0.545	0.587	0.528	0.543	0.575
DUNEM	0.045	0.037	0.030	0.030	0.022	0.026
DDIS	0.068	0.075	0.063	0.069	0.061	0.063
DRET	0.158	0.143	0.183	0.230	0.229	0.193
DTWO	0.204	0.216	0.253	0.230	0.235	0.245

Chapter 4

Comparing Predictions and Outcomes

Household surveys often elicit respondents' intentions or predictions of future outcomes. The survey questions may ask respondents to choose among a selection of (ordered) response categories. If panel data or repeated cross-sections are available, predictions may be compared with realized outcomes. The categorical nature of the predictions data, however, complicates this comparison. Generalizing previous findings on binary intentions data, we derive bounds on features of the empirical distribution of realized outcomes under the "best-case" hypothesis that respondents have rational expectations and that reported expectations are best predictions of future outcomes. These bounds are shown to depend on the assumed model of how respondents form their "best prediction" when forced to choose among (ordered) categories. An application to data on income change expectations and realized income changes illustrates how alternative response models may be used to test the best-case hypothesis.

4.1 Introduction

Subjective data on respondents' intentions or predictions are commonly used for many purposes. For instance, in periods prior to elections, voter polls are held almost continuously and are taken seriously by politicians, journalists, and voters. Economists, however, are quite skeptical of subjective data. It has been claimed, for example, that expectations data need not match up to future outcomes, because there is no incentive for respondents to report expectations accurately (see, for example, Keane and Runkle, 1990).

Some examples in the recent literature, however, suggest that this attitude is changing. Dominitz and Manski (1996, 1997) analyze long-term income expectations of students and near-term income expectations of U.S. households. Guiso et al. (1992, 1996) use expectations data to construct a measure of subjective income uncertainty that is included in models of saving and portfolio choice. In the literature on labor supply, data on desired hours of work have been used to disentangle preferences and hours restrictions (Ilmakunnas and Pudney, 1990, and Euwals and Van Soest, 1996).

If panel data or repeated cross-sections are available, data on expectations of prospective outcomes can be compared with data on realized outcomes. When qualitative rather than quantitative expectations data are to be analyzed, these comparisons may not be straightforward. Manski (1990) studied this problem for the case of a binary outcome. Under the "best-case" hypothesis that respondents have rational expectations and report best predictions of future outcomes, he showed that the expectations data bound but do not identify the probability of each possible outcome.[1]

Say, for example, that households are asked whether or not they intend to buy a new car in the next twelve months. Given their information set, and their (subjective) distribution of future variables that will affect their decisions (income, prices, etc.), they will have some (subjective) probability of buying a car. A possible model for the answer to the intention question is: "yes", if this probability exceeds 0.5, and "no" otherwise. If, for some group of households, the subjective probability is 0.4, they will all answer "no". In general, however, part of the group will actually buy a car. If the subjective distributions of the future variables are correct, and if the realizations of the future variables are independent, about 40% will buy a car. There is thus no reason to expect that the distribution of the intention variable across the population is the same as the distribution of the actual variable. The reason is that the intention reflects some location measure of the household's subjective distribution (for instance, the mode), while the outcome is based upon one draw from the actual distribution. Even in the best-case scenario that subjective and actual distributions coincide, the two variables are not directly comparable.

"Yes/no" expectations about binary outcomes may be thought of as a special case of ordered-category expectations. In particular, they are 2-ordered-category expectations of a variable which takes on just two values (e.g., 0 and 1). We extend Manski's

[1]For more on identification of probabilities, see Manski (1995).

analysis to the general case of multiple-ordered-category expectations of a variable that takes on more than two values. Our empirical analysis, for example, focuses on expectations of the change in household income, which respondents report by choosing among five ordered categories.

We consider three models generating best predictions of the prospective realization. Each model is based on a different expected loss function, which respondents minimize. These behavioral models yield responses of (1) the modal category, (2) the category containing some quantile of the subjective distribution, or (3) the category containing the mean of the subjective distribution. For each case, we derive bounds on features of the distribution of realizations under the best-case hypothesis. In contrast to "yes/no" expectations, different symmetric loss functions may yield different multiple-ordered-category survey responses and therefore imply different best-case bounds. Using panel data or repeated cross-sections, the best-case hypothesis may therefore be tested only under stronger homogeneity assumptions on the expected loss function respondents attempt to minimize. Our analysis illustrates how these tests may be conducted when categorical and/or continuous realizations data are available.

We apply our tests to data on income change expectations and outcomes reported in the 1984 through 1989 waves of the Dutch Socio-Economic Panel (SEP). Heads of households are asked whether they expect their income to decrease strongly, decrease, remain the same, increase, or increase strongly in the next twelve months. A similar ordered-category question is asked about the change in income over the past twelve months. In addition, quantitative reports of the actual income level are given in each interview.

In the majority of empirical life cycle models of consumption and savings, rational expectations of prospective income are taken for granted (see, for example, the survey of Browning and Lusardi, 1996). Our results suggest that in at least four out of the five years considered, the best-case scenario does not hold, and that on average, people have a tendency to underestimate their income change. This means that either households' expectations are not rational, or macro-economic shocks take place in a number of consecutive years, or both. An alternative explanation can be given using an asymmetric loss function: respondents tend to place more weight on negative than positive forecast errors. This will lead to underestimation, on average. Though we find some support for this in our data, our results do not support the best-case hypothesis combined with a uniform asymmetric loss function across the population.

The outline of this chapter is as follows. Section 4.2 discusses the modelling of responses to questions eliciting ordered-category expectations. We consider the expected loss functions that respondents may be minimizing, and we discuss the implications of previous findings in empirical research on expectations data. Section 4.3 derives bounds for conditional probabilities of outcomes, given predictions that should be valid under the best-case hypothesis. These bounds are derived under each of the three response models presented in Section 4.2. Section 4.4 compares the expectations and realizations of income changes across Dutch households. Both categorical and quantitative realizations data are used to test the best-case hypothesis. Section 4.5 concludes.

4.2 Modelling responses to expectations questions

We consider responses to qualitative survey questions eliciting expectations of some outcome y (e.g., the income growth of a household), where respondents must choose among ordered categories. While the number of categories may vary, this type of question is quite common. The questions used to generate both the University of Michigan's Index of Consumer Sentiment and the Conference Board's Consumer Confidence Index include a series of such questions with three ordered categories (see Curtin (1982) and Linden (1982), respectively). Responses of *don't know* are typically accepted, but are often discarded in empirical analyses, as is the case with each of the aforementioned indices.

The next subsection presents several loss functions that respondents may minimize when they answer questions eliciting expectations. Section 4.2.2 gives some examples of expectations research.

4.2.1 Loss functions

As the starting point for analyzing responses to ordered-category expectations questions, consider a respondent who has a subjective probability density $f(y|s)$ over the support of prospective realizations of y given his or her current information captured in variables s. The expectations question asks the respondent to choose one category from K categories $C_1, ..., C_K$, which typically will be of the form $C_k = (m_{k-1}, m_k]$, with $-\infty = m_0 < m_1 < ... < m_{K-1} < m_K = \infty$. The threshold values m_k are not typically defined by the survey question, but are instead subjectively determined (and not reported) by the respondent. The answer to this question is denoted by p.

We propose a model in which p is based upon minimizing some loss function. This interpretation of ordered-category responses follows directly from Manski (1990), who restricts attention to the case of two categories, but the framework is implicit in work dating back at least to Tobin (1959).

Influenced by, for example, the phrasing of the question, the respondent can use various loss functions. If the respondent interprets the K-ordered-category question as one eliciting the most likely outcome, then we may assume he or she will report the category that contains the most subjective probability mass: $p = \text{argmax}_k P\{y \in C_k|s\}$. Choosing the *modal category* corresponds to minimizing subjective expected loss $\mathrm{E}\{1(y \notin C_k)|s\}$ with respect to k.

This modal category response model appears to be sensible, but it is not typically adopted in analyses of ordered-category expectations data.[2] Instead, researchers typically adopt a model in which the respondent forms some point expectation p^* and then chooses the category p that contains p^*. We discuss such models in a framework where the respondent finds the value p^* that minimizes subjective expected loss for some loss function L:

$$\begin{aligned} p^* &= \underset{\pi}{\text{argmin}} \int_{-\infty}^{\infty} L(y-\pi) f(y|s) dy; \\ p &= k \text{ iff } p^* \in C_k. \end{aligned}$$

Researchers often assert that respondents interpret questions of what they "think" or "expect" to happen as questions eliciting the (conditional) mean of y. Such a respondent would choose the category that contains $\mathrm{E}\{y|s\}$. This "category-containing-the-mean" model can be explained if the squared loss function is adopted: $L(u) = u^2$.

It also seems reasonable to assume that respondents may interpret the question as eliciting $\text{Med}\{y|s\}$, the median of $f(y|s)$. This will be the case if the absolute loss function is adopted: $L(u) = |u|$. One may generalize this approach to allow for asymmetric loss functions. In particular, consider respondents who minimize the absolute loss function:

$$L(u) = \alpha|u|1(u \geq 0) + (1-\alpha)|u|1(u < 0), \quad 0 < \alpha < 1.$$

The value p^* which minimizes subjective expected loss is then the α-quantile of $f(y|s)$.

[2] Van der Klaauw (1996) uses this model to interpret responses to unordered-category expectations of occupational choice.

4.2.2 Examples in expectations research

Responses to a binary ("yes/no") intentions question, which may be thought of as a special case of 2-ordered-category expectations questions, have been interpreted in this way, either implicitly or explicitly, by Tobin (1959), Juster (1966), and Manski (1990). The analysis is easier in this case, where y may only take on two values, 0 ("no") or 1 ("yes"). As noted by Manski (1990), this framework requires that responses chosen to minimize subjective expected loss are invariant to the choice of loss function as long as the function is symmetric. Therefore, the modal, mean, and median models described in the previous subsection generate identical responses. In particular, any symmetric loss function dictates that the respondent simply chooses category $k = 1$ ("yes") if $P\{y = 1|s\} > 0.5$ and category $k = 0$ ("no") otherwise.

The response model changes if the respondent weighs prospective losses asymmetrically. Suppose the asymmetric absolute loss function is chosen. Then the respondent chooses $k = 1$ if $P\{y = 1|s\} > \alpha$ and $k = 0$ otherwise. Thus, the asymmetry simply changes the relevant "yes/no" threshold probability.

Carlson and Parkin (1975) study 3-ordered-category inflation expectations data. In our notation, their model rests upon the following two assumptions:

(a) choose category k if $P\{m_{k-1} < y \leq m_k|s\} \geq 0.5 \quad (k \in \{1, 2, 3\})$,

(b) choose *don't know* otherwise.

That is, the respondent chooses one of the three ordered categories if that category contains at least 0.5 probability mass. Otherwise, *don't know* is reported.

The study by Carlson and Parkin represents a rare instance in which *don't know* responses are modeled, and, as such, it does not fall strictly within the framework given above. The model, however, can be seen as a modification of both the modal and median response models. In any K-ordered category case, if one category contains at least 0.5 probability mass, then it is both the modal category and the category that contains the median. If no category satisfies this restriction, then some other response rule must be followed, such as (b) choose *don't know*.

Expectations data have often been used to test predictions of models of rational expectations formation. For surveys of this literature, see Lovell (1986) and Maddala (1994). When ordered-category expectations data are studied, the researcher typically acts as if each respondent chooses the category that contains $\mathrm{E}\{y|s\}$ and then attempts to quantify the qualitative responses (Maddala, 1994). The expectations data are then confronted with subsequent realizations and tests of unbiasedness are conducted. The framework for such an analysis is not always coherently specified in terms of stating (1) the feature of the subjective probability distribution that respondents are assumed to report and (2) the rational expectations implications of the assumed response model. Nerlove (1983), for example, confronts 3-ordered-category expectations data with realizations data provided by French and German firms. He chooses to "regard expectations and plans as single-valued but to recognize that the economic agent knows that they may turn out to be wrong" (p. 1252).

Studies of single-valued quantitative expectations of continuous outcomes typically assume that respondents report the subjective mean (i.e., minimize squared loss). When the frequentist mean of realizations conditional on the value of the subjective expectation differs from that value, it is taken as evidence that respondents form biased expectations. Some researchers have attempted to rationalize such findings by arguing that respondents do not minimize squared loss but instead minimize an asymmetric expected loss function. Leonard (1982), for example, argues that the prospective costs of raising wages (and hiring additional workers) are less than the prospective costs of lowering wages (and firing workers), so firms' wage forecasts appear to be downward-biased.

The remaining sections of this chapter state the implications of rational expectations models for the relationship between K-ordered-category expectations and subsequent realizations, both categorical and continuous. These implications are sensitive to the assumed loss functions and assumptions on variation in the threshold values m_k across individuals and over time.

4.3 Outcome probabilities conditional on predictions

This section generalizes the framework in Manski (1990) and derives restrictions on the distribution of actual outcomes for given values of the subjective predictions in the best-case scenario. We start from the three different assumptions about the respondents' strategy for answering the subjective questions discussed in Section 4.2.1. The three assumptions refer to which feature of the subjective distribution is reflected by p_i, the prediction of respondent i ($p_i \in \{1, ..., K\}$).[3] Section 4.3.1 presents the *modal category* assumption. Section 4.3.2 discusses the α-*quantile* assumption, which for $\alpha = 0.5$ reduces to the *median category* assumption. Section 4.3.3 presents the *mean* assumption.

The observed prediction p_i is always a categorical variable. We distinguish, however, two cases for the realization. We either observe the exact realization y_i, or the category $c_i (\in \{1, ..., K\})$ in which y_i is contained: $c_i = k$ iff $y_i \in C_{k,i}$. If the threshold values are known, observing y_i clearly implies that c_i is also known. In the other case, the c_i may be more informative than the y_i, since they refer to the same categories as the predictions p_i.

Rational expectations means that the respondent's subjective distribution is correct, in the sense that the realization y_i is drawn from the same distribution on which the expectation p_i is based. To test the predictions of rational expectations models, we compare reported predictions with the distribution of realizations across the sample of respondents. This does not exclude common shocks, which would lead to correlation between the y_i for different respondents i. For our test on rational expectations, we need independent realizations across respondents and therefore have to exclude common shocks. Thus if we say we test the best-case scenario, we test the joint null hypothesis of rational expectations and independence of y_i or c_i across respondents.

4.3.1 Modal category assumption

The modal category assumption can be formalized as

$$\mathrm{P}\{c_i = k | s_i, p_i = k\} \geq \mathrm{P}\{c_i = j | s_i, p_i = k\}, \quad j = 1, \ldots, K. \tag{4.1}$$

The probabilities here are computed according to the subjective distribution of respondent i, given the information s_i. As in Manski (1990), let x_i denote some component of s_i that is observed by the econometrician. Using that x_i is contained in s_i, we have

$$\mathrm{P}\{c_i = k | x_i, p_i = k\} \geq \mathrm{P}\{c_i = j | x_i, p_i = k\}, \quad j = 1, \ldots, K. \tag{4.2}$$

Under this model, the best-case scenario implies that, for any group of respondents who report $p_i = k$, a plurality of realizations will fall in category k. Realizations are

[3] We shall work with a random sample of respondents from some (sub)population. The index i refers to the i-th observation in the sample.

based upon drawings from the same distribution leading to the probabilities in (4.1) and (4.2). We can then use observations of c_i to check whether (4.2) holds. Consider the case that x_i is discrete. For notational convenience, assume that x_i and p_i are fixed, and define $P_j \equiv \mathrm{P}\{c_i = j|x_i, p_i = k\}$. Let $\hat{P}_j$ be the sample equivalent of P_j, i.e. the number of observations with $c_i = j$ and $p_i = k$ and the given value of x_i, divided by n, the number of observations with $p_i = k$ and the given value of x_i. Finally, define

$$P \equiv \begin{pmatrix} P_1 \\ \vdots \\ P_K \end{pmatrix}, \qquad \hat{P} \equiv \begin{pmatrix} \hat{P}_1 \\ \vdots \\ \hat{P}_K \end{pmatrix},$$

If there are no macro-economic shocks, the c_i are independent (conditional on x_i and p_i) and the limiting distribution of $\sqrt{n}(\hat{P} - P)$ is $\mathrm{N}(0, \Sigma)$, with the j-th diagonal element of Σ given by $P_j(1-P_j)$ and the (j,k)-th off-diagonal element given by $-P_jP_k$ $(k \neq j)$.

To test the inequality (4.2), we need the categorical information on c_i and not the exact realizations y_i. If we observe only y_i but the threshold values are unknown, the test cannot be performed. The test does not use the ordered nature of the categories; the same procedure can be used for unordered outcomes. Note also that the categories cannot be combined (*ex post*), since this can change the modal category.

4.3.2 α-Quantile category assumption

Now consider the case where the survey response corresponds to the category that contains a point prediction that minimizes some expected loss function. One natural interpretation of p_i is that p_i is the category that contains the α-quantile of the respondent's subjective distribution of y_i. The most obvious choice is $\alpha = 0.5$, in which case p_i is the category containing the median of y_i. Since the categories are ordered, this means that p_i is the median category.

Assume, for convenience, that the subjective distribution of y_i is such that the α-quantile is uniquely defined and corresponds to cumulative probability α, exactly. Let p_i^* denote this α-quantile. In the best-case scenario, the actual outcome y_i is drawn from this same subjective distribution, and thus we have

$$\mathrm{P}\{y_i - p_i^* \leq 0|s_i\} = \alpha. \tag{4.3}$$

If the observed predicted category p_i is equal to k then $p_i^* \in C_{k,i} = (m_{k-1,i}, m_{k,i}]$, so

$$m_{k-1,i} < p_i^* \leq m_{k,i}. \tag{4.4}$$

This implies

$$y_i - m_{k,i} \leq y_i - p_i^* < y_i - m_{k-1,i}.$$

With (4.3), it follows directly that

$$\mathrm{P}\{y_i - m_{k-1,i} \leq 0 | s_i, p_i = k\} < \alpha \leq \mathrm{P}\{y_i - m_{k,i} \leq 0 | s_i, p_i = k\}. \tag{4.5}$$

If y_i itself is observed but the $m_{k,i}$ are unknown, this is of little value without further assumptions on the $m_{k,i}$. We will come back to this in Section 4.4.2. Here, we focus on the case that we observe the category c_i, with $c_i = k$ iff $y_i \in C_{k,i}$. This imposes no restrictions on the $m_{k,i}$ across individuals; all we need is that the outcome variable c_i is based on the same categories as the prediction p_i.

The inequalities in (4.5) can be written as

$$\mathrm{P}\{c_i \leq k-1 | s_i, p_i = k\} < \alpha \leq \mathrm{P}\{c_i \leq k | s_i, p_i = k\}.$$

This implies the following inequalities for the α-quantile category assumption:

$$\mathrm{P}\{c_i > k | x_i, p_i = k\} \leq 1 - \alpha, \tag{4.6}$$

$$\mathrm{P}\{c_i < k | x_i, p_i = k\} < \alpha. \tag{4.7}$$

Under this model, the best-case scenario implies that, for any group of respondents who report $p_i = k$, the α-quantile of the distribution of realizations falls in category k. Therefore, no more than $100\alpha\%$ of realized values are in lower categories and no more than $100(1-\alpha)\%$ are in higher categories.

We can test straightforward whether the inequalities in (4.6) and (4.7) are satisfied for given k and α. For example, with P_j and $\hat{P}_j$ defined as in Section 4.3.1, a test of (4.6) can be based upon

$$\sqrt{n}\left(\sum_{j=k+1}^{K} \hat{P}_j - \sum_{j=k+1}^{K} P_j\right) \xrightarrow{\mathcal{L}} \mathrm{N}\left(0, \left(1 - \sum_{j=k+1}^{K} P_j\right) \sum_{j=k+1}^{K} P_j\right). \tag{4.8}$$

Unlike the test in the previous subsection, this test uses the ordering of the categories. This suggests that the required assumptions are stronger than those used for the modal category assumption. But for the case that $\alpha = 0.5$ (median category assumption), we see that (4.6) and (4.7) for all k do not imply that (4.2) holds for all k and j, and vice versa. It is true, however, that for $k = 1$ (i.e., the lowest category)

(4.6) implies (4.2) and for $k = K$ (i.e., the highest category) (4.7) implies (4.2). Thus the median category assumption is stronger than the modal category assumption in the sense that it imposes sharper lower bounds on the probabilities that the extreme predictions (i.e., k equals either 1 or K) are realized. The modal category assumption always requires a plurality of probability mass in the predicted category, whereas the median category requires a majority, when either the lowest or highest category is predicted.[4]

4.3.3 Mean assumption

The third interpretation of what respondents may have in mind when they provide their subjective prediction is that p_i is the category that contains $\mathrm{E}\{y_i|s_i\}$, the subjective mean of y_i. As in the previous subsection, $p_i = k$ implies equation (4.4). Thus

$$\mathrm{E}\{y_i|s_i, p_i = k\} \in (m_{k-1,i}, m_{k,i}],$$

and also

$$\mathrm{E}\{y_i|x_i, p_i = k\} \in (m_{k-1,i}, m_{k,i}]. \tag{4.9}$$

Under this model, the best-case scenario implies that, for any group of respondents who report $p_i = k$, the mean of the distribution of realizations falls in category k.

A drawback of the mean assumption is that categorical information on y_i is not sufficient to test the best-case scenario. Actual values of y_i and information on the threshold values $m_{k,i}$ are required. If the $m_{k,i}$ are known and if i.i.d. observations y_i are available, (4.9) can be used to construct a test, based upon the standard asymptotic behavior of a sample mean (conditional upon x_i). If the $m_{k,i}$ are unknown but some prior information on them is available, we may still be able to carry out a test based upon a sample mean of the y_i. We come back to this in the empirical application in Section 4.4.2.

4.4 Application to income change predictions

We apply the tests for the best-case scenario developed in the previous section to data on income change predictions and realizations. The data are taken from the

[4]If $K = 3$, we also have that, for $k = 2$, (4.2) implies (4.6) and (4.7). In that case, therefore, the modal category assumption imposes a stronger restriction for intermediate predictions than does the median category assumption.

1984 – 1989 waves of the Dutch Socio-Economic Panel (SEP), an unbalanced panel of households in the Netherlands. The same data are used in Chapter 3. Heads of households are asked to answer similar questions on realized income changes and future income changes. The question on the future is given by

> *What will happen to your household's income in the next twelve months? Possible answers are: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).*

The answer to this question of head of household i in the sample is denoted by p_i. In each wave, heads of households are also asked what *happened* to their household income in the last twelve months. This question is formulated in the same way as the one on future income, with the same categories as possible answers. The answer is denoted by c_i. Since the questions are similar, and the question on p_i immediately follows the question on c_i, it seems reasonable to assume that the respondents use the same income concept for both answers. We thus compare p_i in wave t with c_i observed in wave $t+1$ (t= '84, '85, '86, '87, '88). The next subsection discusses the tests based upon the qualitative data. Apart from that, we have quantitative information on household income from various sources, from which we construct a continuous measure of realized income change. These quantitative data will be used in Section 4.4.2.

4.4.1 Qualitative data on realized income

Modal category assumption

Under the best-case hypothesis of rational expectations and statistically independent realizations, frequencies of the income growth categories can be used to estimate the probabilities in (4.2) for the modal category assumption. Table 4.1 displays the frequencies for five combinations of adjacent years (ranging from 1984 through 1989). We present frequencies that are not conditional on other covariates, so x_i is "year of observation." Since the SEP is an unbalanced sample, the numbers of observations per wave are different (see the final column of Table 4.1).

Table 4.1 : Estimates of $P\{c_i = c|p_i = k\}$ (in percentages), where k stands for *predicted* category and c for *realized* category of income change

		$c=1$	$c=2$	$c=3$	$c=4$	$c=5$	$n^{*)}$
$k=1$:	'84 - '85	29.7	26.7	31.7	10.9	1.0	101
strong decrease	'85 - '86	42.1	15.8	28.9	13.2	0.0	38
	'86 - '87	24.5	28.6	32.7	8.2	6.1	49
	'87 - '88	32.4	19.1	41.2	2.9	4.4	68
	'88 - '89	41.5	9.8	29.3	17.1	2.4	41
	pooled	32.7	21.5	33.3	9.8	2.7	297
$k=2$:	'84 - '85	10.6	24.6	53.2	10.0	1.6	549
decrease	'85 - '86	10.6	24.7	51.6	10.6	2.4	376
	'86 - '87	12.2	35.7	42.7	7.8	1.7	361
	'87 - '88	7.5	20.3	61.4	8.7	2.0	492
	'88 - '89	9.4	21.6	53.5	13.6	1.9	361
	pooled	10.0	25.0	53.1	10.1	1.9	2139
$k=3$:	'84 - '85	3.0	10.4	68.8	15.0	2.8	808
no change	'85 - '86	2.4	8.7	66.0	20.1	2.8	1313
	'86 - '87	3.5	13.7	64.1	16.4	2.3	1919
	'87 - '88	2.2	7.1	70.2	16.8	3.8	1944
	'88 - '89	1.7	5.5	67.9	21.0	3.9	2232
	pooled	2.5	8.8	67.3	18.2	3.2	8216
$k=4$:	'84 - '85	3.9	7.7	28.7	48.1	11.6	181
increase	'85 - '86	0.9	3.2	34.8	50.0	11.1	342
	'86 - '87	1.8	5.7	37.8	43.9	10.8	492
	'87 - '88	1.8	4.1	37.0	44.3	12.8	508
	'88 - '89	2.1	3.6	26.0	52.8	15.5	561
	pooled	1.9	4.5	33.2	47.7	12.7	2084
$k=5$:	'84 - '85	0.0	0.0	25.0	12.5	62.5	8
strong increase	'85 - '86	0.0	0.0	33.3	16.7	50.0	18
	'86 - '87	0.0	7.1	28.6	21.4	42.9	14
	'87 - '88	6.7	0.0	13.3	26.7	53.3	15
	'88 - '89	0.0	4.2	25.0	25.0	45.8	24
	pooled	1.3	2.5	25.3	21.5	49.4	79

*) $n = \#\{i : p_i = k\}$

Table 4.1 shows that, for $k = 1$ (strong decrease predicted), the inequality (4.2) is not satisfied in three years: in '86-'87 the frequencies for $c = 2$ and $c = 3$ exceed the frequency for $c = 1$, in '84-'85 and '87-'88, this holds for the frequency for $c = 3$ only. None of these results, however, are significant (nor is it the case for the data pooled across years). For $k = 2$, however, the findings are stronger, possibly due to the larger numbers of observations. The inequalities are violated for each year: of those who predict a moderate income fall, the number of households who actually experience no change is larger than the number whose incomes moderately fall. This is significant in four of the five years. The result is also significant in case of the pooled data. The systematic violation of inequality (4.2) suggests that either the modal category assumption is not relevant or the best-case scenario is not realistic. For $k = 3$, $k = 4$, and $k = 5$, we find no violations of (4.2).

We also calculated the estimates in Table 4.1 conditional on several covariates x_i, such as the level of net household income, dummies for realized income changes in the past twelve months (lagged values of c_i), sex of the head of household, and dummies for the labor market state of head and spouse. For a continuous x_i it is possible to summarize the continuous variable into groups, for instance, low and high income groups. It is also possible to use nonparametric estimates (see, e.g., Härdle and Linton, 1994).

The overall conclusion of the conditional analysis is that the pattern in Table 4.1 remains basically the same if subsamples with given values of x_i are used. For almost all x_i and combinations of adjacent years, the estimate of $\mathrm{P}\{c_i = 3|x_i, p_i = 2\}$ is higher than that of $\mathrm{P}\{c_i = 2|x_i, p_i = 2\}$. The results are not always significant, but this may be due to the small numbers of observations in some of the subsamples. Thus, the violation of (4.2) cannot be ascribed to one specific income category, to households with a specific composition or labor market state, or to households whose incomes fell in the past.

Median and other quantile category assumptions

This subsection first tests the inequalities (4.6) and (4.7) for the median: $\alpha = 0.5$. For the case x_i includes "year of observation" only, the tests for the best-case scenario under the median category assumption can be derived from the data in Table 4.1. By adding up the relevant probabilities and replacing the unknown variance in (4.8) with a consistent estimate, we can construct confidence intervals for the probabilities in (4.6) and (4.7). Table 4.2 displays (two-sided) 90% confidence intervals. (Note that we perform one-sided tests, with significance level equal to 5%.)

Table 4.2 : 90% confidence intervals for the (cumulative) probabilities (in percentages)

		$P\{c_i < k \vert p_i = k\}$		$P\{c_i > k \vert p_i = k\}$		$n^{*)}$
		lower	upper	lower	upper	
$k = 1$: strong decrease	'84 - '85	–	–	62.8	77.8	101
	'85 - '86	–	–	44.7	71.1	38
	'86 - '87	–	–	65.4	85.6	49
	'87 - '88	–	–	58.3	77.0	68
	'88 - '89	–	–	45.9	71.2	41
	pooled	–	–	62.9	71.8	297
$k = 2$: decrease	'84 - '85	8.4	12.7	61.5	68.2	549
	'85 - '86	8.0	13.3	60.6	68.7	376
	'86 - '87	9.4	15.0	47.8	56.4	361
	'87 - '88	5.6	9.5	68.8	75.5	492
	'88 - '89	6.9	11.9	65.0	73.0	361
	pooled	8.9	11.0	63.3	66.7	2139
$k = 3$: no change	'84 - '85	11.4	15.3	15.6	20.0	808
	'85 - '86	9.6	12.5	21.0	24.8	1313
	'86 - '87	15.8	18.6	17.2	20.2	1919
	'87 - '88	8.2	10.3	19.1	22.1	1944
	'88 - '89	6.3	8.1	23.4	26.4	2232
	pooled	10.7	11.8	20.7	22.2	8216
$k = 4$: increase	'84 - '85	34.3	46.3	7.7	15.5	181
	'85 - '86	34.6	43.2	8.3	13.9	342
	'86 - '87	41.6	49.0	8.5	13.1	492
	'87 - '88	39.3	46.5	10.4	15.2	508
	'88 - '89	28.5	35.0	13.0	18.0	561
	pooled	37.8	41.3	11.5	13.9	2084
$k = 5$: strong increase	'84 - '85	9.3	65.7	–	–	8
	'85 - '86	30.6	69.4	–	–	18
	'86 - '87	35.4	78.9	–	–	14
	'87 - '88	25.5	67.9	–	–	15
	'88 - '89	37.4	70.9	–	–	24
	pooled	41.4	59.9	–	–	79

*) $n = \#\{i : p_i = k\}$

For $k = 1$ the hypothesis $P\{c_i > k|p_i = k\} \leq 0.5$ is rejected in three years: three confidence intervals do not contain the value 0.5, and inequality (4.6) is violated significantly. This also holds for the data pooled across years. For $k = 2$, four of the five probabilities are significantly larger than 0.5. For $k = 5$, (4.6) is violated twice, but in neither of the two cases is this significant. The conclusions are therefore similar to those in the previous subsection. Those who expect a moderate decrease appear, on average, to be too pessimistic.

If we repeat the calculations conditional on certain values of covariates, the results are somewhat clearer than for the modal category assumption. Partitioning according to income level, we find that, for those who predict their income to fall, (4.7) is often violated significantly for the lower and intermediate income quartiles, but less so for the highest income quartile. For the lowest income quartile, we also find for two years significant violations of (4.6) for those who predict a moderate income rise. This group, in particular, seems too often to expect a (positive or negative) income change. A similar conclusion can be drawn for those who did not experience an income change in the previous year. For $k = 3$, the category with the highest number of observations, the data respect both inequalities, indicating that for the groups who predict their income to be stable, the best-case hypothesis cannot be rejected.

Under the median category assumption, the best-case scenario is rejected for several groups. Table 4.2 also allows testing under α-quantile category assumptions for other values of α. For each separate row in the table, the confidence intervals together with the inequalities (4.6) and (4.7) allow us to determine ranges of α for which the best-case scenario is not rejected. For example, the third row implies that the best-case scenario is rejected for $\alpha > 0.346$.

In some years, the ranges of α for which the best-case scenario is not rejected do not overlap. In '86-'87, for example, $\alpha \leq 0.346$ is obtained from $P\{c_i > 1|p_i = 1\}$, while for $P\{c_i < 4|p_i = 4\}$, we get $\alpha \geq 0.416$. A similar result is found for '87-'88 and '88-'89. This means that our data do not support the best-case hypothesis combined with a uniform asymmetric loss function based upon a single value of α per year. For '84-'85 and '85-'86, the bounds do not conflict with each other and the results support the best-case scenario with a value of α less than 0.5. The interpretation of this is that respondents tend to place more weight on negative forecast errors ($y_i - p_i < 0$). This leads, on average, to underestimation.

4.4.2 Quantitative data on realized income

Mean assumption

The categorical information on y_i is not enough to test the best-case hypothesis under the assumption that p_i reflects the category containing the mean. Instead of c_i, we need y_i itself. The SEP contains detailed information on income from about twenty potential sources for each household member. After-tax household income is constructed by adding up all income components of all family members. The change in household income is then obtained by comparing household income in two consecutive waves.[5]

The subjective questions on past and future income changes are not precise. It is not clear whether households should consider real or nominal income, absolute or percentage changes, or which threshold values $m_{k,i}$ they should use to distinguish between a strong change, a moderate change, and no change. In the previous subsections, additional assumptions on all this were not needed. The only necessary assumption was that heads of households use the same concept for predicted and realized income changes. To use the quantitative measure of household income, however, additional assumptions cannot be avoided.

It appears that, whichever concept of income change is used, the income change variable suffers from enormous outliers. This has strong effects on the means for the subsamples with given income change prediction. Many of them are estimated inaccurately, and carrying out the tests based upon (4.9) does not lead to meaningful results (details are available upon request).

A practical solution to this problem is to remove the observations in the upper and lower tails of the distribution of the income change variable. Tables 4.3 and 4.4 delete the 5% lowest and 5% highest observations.[6]

Table 4.3 assumes that households consider absolute changes, and looks at nominal as well as real changes. Table 4.4 does the same for percentage income changes. Both tables present estimates of the mean and their standard errors for all values of p_i and all years.[7] As in Tables 4.1 and 4.2, the only covariate we condition on is the year of observation.

[5] See Appendix 3.B and 3.C in Chapter 3.

[6] This is done for each income change variable and each year separately, without partitioning according to p_i.

[7] Standard errors are not corrected for the trimming procedure.

Table 4.3 : 5%-Trimmed sample means of the (actual) absolute change in income per prediction category k (standard errors of sample means in parentheses)

ABSOLUTE CHANGE						
		nominal		real		$\#\{i : p_i = k\}^{*)}$
'84 - '85	$k = 1$	-97.9	(632.5)	-902.9	(625.7)	88
	2	1177.2	(216.8)	352.1	(215.7)	503
	3	1417.0	(197.1)	575.3	(194.1)	727
	4	1967.0	(467.2)	1112.2	(449.4)	156
	5	1801.7	(2611.4)	928.1	(2717.9)	7
'85 - '86	$k = 1$	-3348.4	(1264.0)	-3409.9	(1265.3)	35
	2	-685.3	(319.5)	-746.6	(319.1)	338
	3	456.6	(154.5)	389.2	(154.2)	1189
	4	2338.1	(327.3)	2258.0	(327.0)	302
	5	5598.2	(1749.1)	5525.4	(1749.2)	13
'86 - '87	$k = 1$	-192.1	(1137.3)	-125.4	(1139.6)	41
	2	695.3	(379.5)	704.8	(382.5)	326
	3	1148.7	(152.6)	1228.1	(152.6)	1743
	4	1519.4	(313.2)	1599.7	(313.6)	430
	5	9100.4	(1694.1)	9198.7	(1703.6)	11
'87 - '88	$k = 1$	-2794.0	(782.5)	-3037.9	(782.7)	61
	2	-136.7	(272.3)	-376.5	(271.0)	452
	3	536.6	(146.2)	219.6	(145.0)	1745
	4	1645.1	(260.0)	1307.0	(259.4)	453
	5	1187.7	(2211.1)	786.4	(2225.1)	12
'88 - '89	$k = 1$	-3618.2	(1372.3)	-4076.3	(1372.7)	35
	2	-181.7	(335.5)	-636.6	(334.5)	325
	3	1236.1	(133.7)	692.3	(132.6)	2025
	4	2404.1	(274.9)	1716.9	(272.0)	490
	5	3734.4	(1809.5)	3004.8	(1791.5)	22

*) The outliers are determined separately for the nominal and real change. Since the difference in number of observations in a specific category k is at most one observation, we present only the number of observations for the real change.

The standard errors are quite large. To obtain standard errors for the differences between two means for different values of k, the corresponding variance estimates can be added, due to independence (means for different values of k are based upon disjoint sets of observations). In many cases, the means for consecutive values of k are not significantly different.

Table 4.4 : 5%-Trimmed sample means of the (actual) change in income, in terms of percentages, per prediction category k (standard errors of sample means in parentheses)

CHANGE IN TERMS OF PERCENTAGES						
		nominal		real		$\#\{i : p_i = k\}$
'84 - '85	$k = 1$	0.7	(2.1)	-1.8	(2.0)	90
	2	4.5	(0.7)	1.9	(0.7)	499
	3	5.5	(0.6)	2.9	(0.6)	725
	4	9.0	(1.4)	6.3	(1.3)	161
	5	0.8	(5.8)	-1.6	(5.6)	6
'85 - '86	$k = 1$	-7.1	(3.1)	-7.3	(3.1)	33
	2	-0.8	(0.9)	-1.0	(0.9)	332
	3	2.2	(0.5)	2.0	(0.5)	1190
	4	8.3	(1.0)	8.1	(1.0)	310
	5	13.2	(5.2)	13.0	(5.1)	12
'86 - '87	$k = 1$	0.7	(4.1)	0.9	(4.1)	45
	2	3.7	(1.2)	3.9	(1.2)	320
	3	4.9	(0.5)	5.1	(0.5)	1730
	4	7.2	(1.1)	7.4	(1.1)	444
	5	28.7	(4.8)	28.9	(4.8)	12
'87 - '88	$k = 1$	-5.0	(2.5)	-5.9	(2.5)	63
	2	1.8	(0.8)	0.9	(0.8)	435
	3	2.7	(0.5)	1.8	(0.5)	1748
	4	4.9	(0.8)	4.0	(0.8)	465
	5	7.2	(5.6)	6.2	(5.6)	12
'88 - '89	$k = 1$	3.7	(4.9)	2.1	(4.8)	31
	2	1.5	(1.1)	-0.1	(1.1)	312
	3	6.0	(0.4)	4.3	(0.4)	2017
	4	8.7	(0.9)	7.0	(0.9)	516
	5	20.0	(6.3)	18.1	(6.2)	21

The inequalities (4.9) imply that, for n large enough, we would expect that the sample means increase with k.[8] This is usually the case. Only for the extreme predictions ($k = 5$ in Table 4.3 and $k = 1$ or $k = 5$ in Table 4.4) is this violated in various years – but never significantly. More specific tests can be carried out if prior information on the threshold values $m_{k,i}$ is used. For example, it seems reasonable to assume that $m_{1,i}$ and $m_{2,i}$ are negative, while $m_{3,i}$ and $m_{4,i}$ should be positive, implying that the means for $k = 1$ and $k = 2$ should be negative, and those for $k = 4$

[8] This will certainly be the case if the threshold values are constant across individuals, but may not be the case if there exists a negative correlation between the thresholds and p_i.

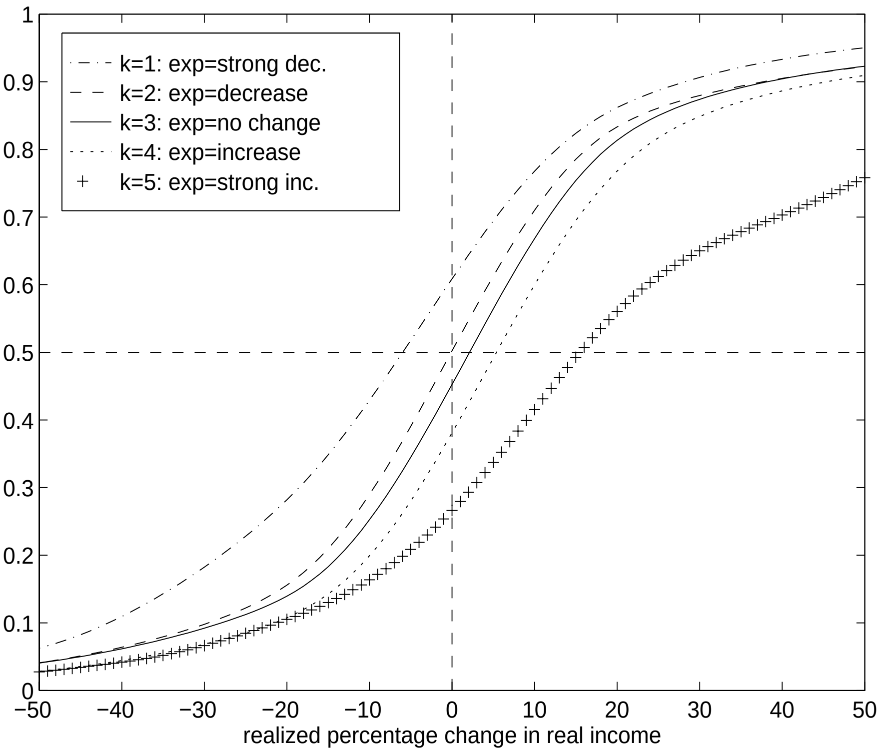
and $k = 5$ should be positive. For $k = 1$, there are some positive values, but they are never significantly different from 0. For $k = 2$ however, we find significant violations, particularly in Table 4.4, for the nominal as well as the real percentage income change. For $k = 3$, $k = 4$, and $k = 5$, the means are always positive. Thus, as in the previous subsections, the conclusion can be drawn that the group of households expecting a moderate decrease is overly pessimistic, on average.

α-Quantile category assumption

Using the quantitative data on income changes, we can also (nonparametrically) estimate the cumulative distribution function (cdf) of the realized income change conditional on the expected income change category. From now on, we assume that the threshold values are constant across time and individuals, and use the pooled data set. Figure 4.1 presents the cdf's of the realized percentage real income change (y_i) for given expected income change category (p_i). The cdf's for higher p_i are to the right of those with lower p_i, confirming that those who are more optimistic have a higher probability of a change exceeding a%, for each a. The same pattern tends to be found for the years separately.[9]

[9] In a few cases the monotonicity is violated by the extreme categories, probably due to the low number of observations. All figures are presented in Appendix 4.A.

Figure 4.1 : Estimated cumulative distribution functions of the realized percentage change in real income, conditional on the expected income change category for the data pooled across years



Let us assume that the best-case scenario holds. From Section 4.3.2 we know that the α-quantile assumption then implies

$$P\{y_i \leq m_{k-1} | p_i = k\} < \alpha \leq P\{y_i \leq m_k | p_i = k\}. \tag{4.10}$$

If $\xi_{\alpha,k}$ denotes the α-quantile of y_i conditional on $p_i = k$, this can be written as

$$m_{k-1} < \xi_{\alpha,k} \leq m_k.$$

For $\alpha = 0.5$, Figure 4.1 shows that $\xi_{\alpha,2}$ is about zero, suggesting that m_2 is nonnegative. This seems unreasonable, since it would lead to the implausible asymmetry that the no change category $(m_2, m_3]$ contains nonnegative changes only.[10] An explanation could be that α is less than 0.5.

To make this more precise, we calculated [11] confidence intervals for $\xi_{\alpha,k}$ ($k = 1, ..., 5$) for $\alpha = 0.5$ and $\alpha = 0.425$. Table 4.5 displays the results. Combining Table 4.5

[10]Working with nominal instead of real changes makes the asymmetry even stronger.

[11]We used the quantile regression in STATA and regressed the realized percentage change in real income on a constant. Standard errors are calculated by bootstrapping, with 1000 replicated bootstrap samples. See Gould (1992) for details.

with (4.10) leads to 95% one-sided confidence bands for m_k, under the best-case scenario and the α-quantile assumption. For example, $\alpha = 0.5$ implies $m_2 \geq -0.33$, and $m_3 \geq 1.31$. Thus $\alpha = 0.5$ does not allow that the no change interval $(m_2, m_3]$ is symmetric around zero. On the other hand, for $\alpha = 0.425$ we find $m_2 \geq -1.82$ and $m_3 \geq -0.18$, and symmetry is possible. This suggests that respondents might use an asymmetric loss function. Unlike the case with the qualitative data, we now find that there are values of α that do not lead to evidence against the best-case scenario.

Table 4.5 : 90% confidence intervals for $\xi_{\alpha,k}$; pooled data set

	$\alpha = 0.50$		$\alpha = 0.425$	
	lower	upper	lower	upper
strong decrease	-6.38	-2.69	-10.7	-4.57
decrease	-0.33	0.14	-1.82	-1.11
no change	1.31	1.71	-0.18	0.14
increase	4.25	5.28	2.35	3.22
strong increase	9.17	18.5	5.89	14.8

4.5 Conclusions

Manski (1990) has compared realizations with predictions for the case of two possible outcomes. We have generalized his framework to the case of more than two outcomes. We discuss which assumptions are necessary to derive bounds on the theoretical relationship between expectations and realizations under the best-case scenario of rational expectations and statistically independent realizations across individuals. We have focused on the case of ordered outcomes that can be interpreted as categories of an underlying continuous variable. Unlike in Manski's case, it appears that the inequalities to be tested are sensitive to the assumption on the location measure of the subjective distribution of the variable of interest reflected by the subjective prediction. We discussed three possibilities: the modal category, the median or α-quantile, and the mean assumption. The former two can be applied if comparable categorical data on predictions and outcomes are available, while the latter can only be applied if the actual outcome is measured as a continuous variable. The three assumptions lead to different bounds, none of them uniformly sharper than any of the others.

The tests are applied to Dutch household data on predicted and actual income changes, using panel data for 1984 to 1989. On the basis of the categorical realizations data, we find the same results for the modal and median category assumption: the best-case hypothesis is rejected for the group of households expecting a moderate income decrease. For too many of these, the realization is "no change". This result has various interpretations. One is that observations are not independent, due to common shocks. That this result is obtained for a number of years reduces the plausibility of this explanation. A second interpretation is that people have asymmetric loss functions. We investigated this with more general α-quantile assumptions. Using the categorical realizations, we found that there is no single value of α that can explain the data for all years under the best-case scenario. Using an alternative continuous measure of household income change, however, we concluded that values of α lower than 0.5 could be plausible. A third explanation is that substantial groups of households do not have rational expectations.

To make a definite choice between these interpretations of our findings, we seem to need more research, for example based upon data with more detailed information on individuals' subjective income distribution. Such data are now collected in the Dutch VSB-panel (see Chapter 5), the American Survey of Economic Expectations (Dominitz and Manski, 1997), and the Italian Survey of Household Income and Wealth (Guiso et al., 1992).

4.A Appendix

This appendix presents figures of the estimated cumulative distribution functions of the realized percentage change in real income conditional on the expected income change category for the years separately (see also Section 4.4.2, Figure 4.1).

Figure 4.A.1 : 1984–1985

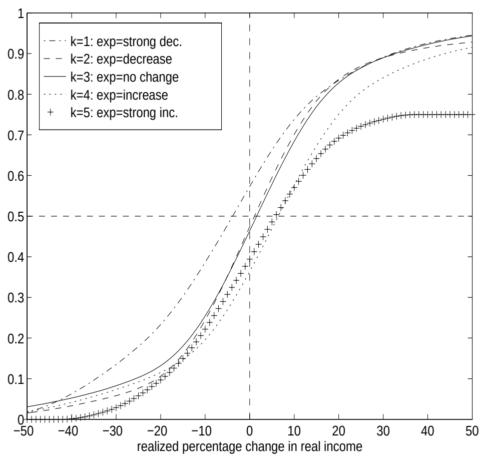


Figure 4.A.2 : 1985–1986

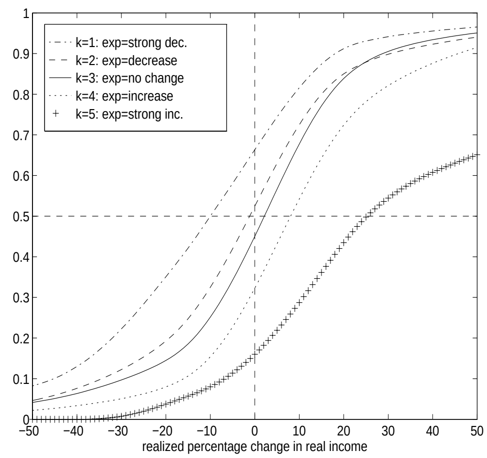


Figure 4.A.3 : 1986–1987

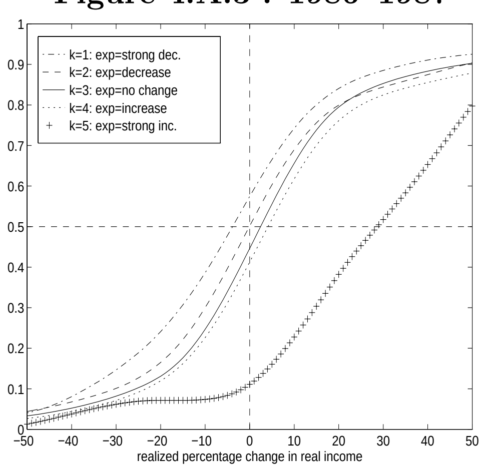


Figure 4.A.4 : 1987–1988

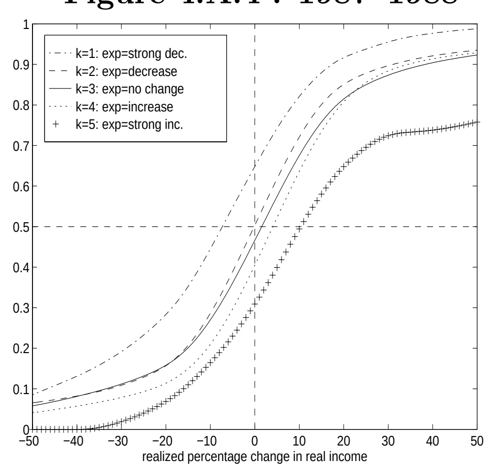
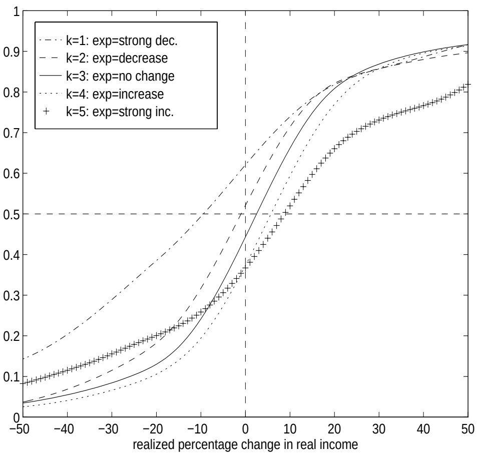


Figure 4.A.5 : 1988–1989



Chapter 5

How certain are Dutch households about future income?

The growing literature on precautionary saving clearly indicates the need for measurement of income uncertainty. This chapter empirically analyzes subjective income uncertainty in the Netherlands. Data come from the Dutch VSB panel. We measure income uncertainty directly by asking questions on expected household income in the next twelve months. First, we describe our data and compare a measure of income uncertainty with corresponding studies conducted in the U.S. and Italy. Second, we investigate the relationship between the measure of income uncertainty and some household characteristics. Controlling for information on expected changes, we find strong relationships between labor-market characteristics and the subjective income uncertainty as reported by the heads of households.

5.1 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 (cf. Kimball, 1990), several papers have addressed the theoretical result that consumers postpone their consumption when income becomes more risky. See e.g. Guiso et al. (1992), Lusardi (1993), and Banks et al. (1995). 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.

Most of the empirical studies in which income uncertainty is involved 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 use all kind of proxies for uncertainty of future income. At the cross-sectional level, however, indicators for risk are subject to a problem of self-selection.[1] In a life cycle framework, the standard approach is to infer income expectations and income uncertainty from panel data on realizations. An explicit model of the process of expectation formation is then specified. The major disadvantage of this method is the necessity of relying on the model of how expectations are formed. Moreover, shocks in the process that generates income might be completely predicted by the respondent. For example, when a head of household knows for sure that the partner will quit his or her job next year, no uncertainty is involved, while subsequent realizations of household income will show a large variation.

Given the unobservable nature of households' subjective assessments of specific risks, Guiso et al. (1992) argue that there is no alternative but to rely upon direct measurement of households' perceived uncertainty. Recent work on the subjective measurement of income expectations has indicated that survey data can provide useful information (see e.g. Dominitz and Manski, 1997). Chapter 3 showed that the relation between answers to subjective survey questions on income expectations and various background variables are rather robust over time and of the expected sign.

This chapter focuses on some measures of uncertainty of future income based on subjective data. In attempting to explain relationships between the subjective uncertainty and some household characteristics, our approach follows the study by Dominitz and Manski (1997, DM97 in the sequel), who collected data on the one-year-ahead income expectations on the household level of members of American households

[1] Households in risky categories may have chosen to belong to that category simply because they are less risk-averse. Occupational dummies to classify households in different risk categories then give a wrong indication for perceived income uncertainty.

[Survey of Economic Expectations (SEE)]. Based on the answers of 437 respondents, they find a substantial variation in income uncertainty. We will use the third wave of a Dutch panel data set: the VSB panel[2] (in this wave the questions we will use are asked for the first time). The panel contains information on more than 2500 households and consists of two subpanels. One is designed to be representative of the whole Dutch population and the other is a random sample from households in the upper 10% of the income distribution in the Netherlands. All participating households have been provided with a personal computer and answer the survey questions directly on their PC. No personal interviews are held.

DM97 compare their study with Guiso et al. (1992), who investigate income uncertainty in Italy. Although aware of the fact that the two survey methods were not the same, they argue that it is tempting to conclude that U.S. households perceive far more income uncertainty than do those in Italy. Results based upon our survey data suggest that also in the case of Dutch households the perceived income uncertainty is lower than in case of U.S. households.

The outline of this chapter is as follows. Section 5.2 discusses the questions posed in the VSB panel to elicit information about subjective income uncertainty. In particular, we will examine two different types of questions: one that is qualitative in nature and a second question that elicits information on income uncertainty in a quantitative way. Section 5.3 will present the data. Here, the answers to the quantitative questions will be used to derive some measures of income uncertainty that will be compared with those obtained in previous studies. The quantitative measure is also briefly compared with a qualitative measure of income uncertainty. Section 5.4 estimates a regression model for the location and scale of the subjective income distribution. Section 5.5 concludes.

5.2 Data from the VSB panel

The VSB panel started in 1993. The survey method is completely computerized. Each household is provided with a personal computer with a modem. Questions and answers are transferred via the computer. If the respondent has questions or problems, he may call a helpdesk.

The data that we will use are taken from the third wave of the panel. These data

[2]The VSB panel has been supported by the VSB Foundation, which explains its name.

were collected in 1995 and contain information about 2574 heads of households.[3] The VSB panel consists of two parts. One is designed to be representative for the whole Dutch population, the other one is a random sample of households in the upper 10% of the income distribution in the Netherlands. The information in the data set can be divided into seven parts: household characteristics, housing, labor-market status and pension entitlements, health, income, assets and liabilities, and economic and psychological concepts. Our analysis draws heavily upon the parts concerned with household characteristics, income, and economic and psychological concepts.

The 1995 wave contains two blocks of questions related to the measurement of subjective income uncertainty. The first one consists of qualitative questions and the second one consists of quantitative questions similar to those in DM97. We will discuss both types of questions in the next two subsections.

5.2.1 Qualitative measurement of uncertainty

All questions in the survey concerning future income are on the household level. Respondents are asked what will happen to their net household income in the next twelve months.[4] First they are asked to indicate whether it will decrease, stay the same or increase. After that, when they indicate they expect a change in income, they are asked by which percentage they think their net household income will change. These questions refer to the location of their distribution of future income and are unrelated with uncertainty. Seven questions related to uncertainty about future income follow directly after the previously mentioned questions. First, respondents are asked how probable an income increase of more than 15% is. They can answer on a seven-point scale ranging from very unlikely to very likely.[5] The same type of question is asked for an increase of between 10% and 15%, between 5% and 10%, no change, a decrease of between 5% and 10%, a decrease of between 10% and 15% and a decrease of more than 15%.

An extensive literature exists on quantifying verbal probability questions. See, among others, Reagan et al. (1989), and Mosteller and Youtz (1990). The former examine the meanings of 18 verbal probability expressions and conclude that some

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

[4]For the precise wording of the questions, see Appendix 5.A.

[5]Respondents get some information on how to interpret the scale. However, only the end-points of the seven-point scale have a verbal label.

areas of the probability range are not so well captured. The latter try to quantify the meanings of 52 qualitative probabilistic expressions. In a comment on this paper, Kadane (1990) argues that significantly fewer than 52 words are needed. He summarizes the findings of Mosteller and Youtz into eleven verbal descriptions that cover the whole range of possible probabilities.

In this literature, some authors prefer verbal, nonnumerical terms for communicating uncertain opinions. Wallsten et al. (1986) argue that most people feel that they better understand words than numbers. On the contrary, Beyth-Marom (1982) highlights the communication problems caused by verbal probability expressions. In addition to the better communication achieved by numerical expressions, another advantage is the possible application of various quantitative methods.

This chapter focuses on the quantitative expressions, since to the best of our knowledge, no work has been done on deriving a (characteristic of the) subjective probability distribution from verbal questions. The end of Section 5.3 briefly compares a measure of uncertainty derived from the qualitative questions mentioned above and a measure of uncertainty derived from the quantitative questions.

5.2.2 Quantitative measurement of uncertainty

The qualitative type of questions mentioned in the previous subsection are asked in each wave of the VSB panel. Since 1995 there are also questions in the panel that try to elicit the subjective distribution of future income in a quantitative way. First, the respondents are asked about the range in which their household income will fall in the next twelve months. The precise wording of the 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 the highest possible income. [6] 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 $\mathrm{PRO}_1, \ldots, \mathrm{PRO}_4$ and correspond to values of the subjective distribution function of next year's household income.

Similar questions are used by DM97 to investigate income expectations. The first difference between our data and the data from the 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 realizations, there will be no anchoring effect present in our data.[7] 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 household is certain about the household income in the next twelve months (say the difference between highest and lowest possible income is Dfl. 2,000), 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

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

[7] Anchoring means that a respondent adapts 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 might 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 these values are objectively reasonable.

be pursued in the next wave of the VSB panel. For the current wave we will have to ignore the respondents who provided an inconsistent sequence of probabilities.

5.3 Measurement of subjective income uncertainty

For the measurement of the subjective income uncertainty we will use the quantitative questions described in Section 5.2.2. These questions can be found in the income part of the panel. The 1995 wave of the panel consists of 2574 heads of households.[8] Only 1614 of them answer affirmatively a question on whether or not they have an idea about their household's income in the past year. These heads of households all answer the question of what the household's lowest and highest possible income for the next year will be. 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, 1504 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 households are asked to evaluate the probability with which their household income will fall below a certain level (see Section 5.2.2). Four questions of this type are asked, and in theory, the given probabilities should result in a non-decreasing sequence of answers. This is not true for 220 of the heads of households, while two heads of households do not answer the questions. In addition to the questions from the income part of the questionnaire, also some questions from the economic and psychological part will be used. These questions are related to realized and expected income changes of the household's income (see Section 5.2.1). Due to some missing observations, our final data set consists of 1127 heads of households, with completely observed information from both parts of the questionnaire.

Some descriptive statistics concerning both the lowest and highest possible income and the probabilities (in percentages) are given in Table 5.1. We distinguish between the representative and high-income part of the panel to see whether there are systematic differences.

The numbers in Table 5.1 indicate that there is substantial variation in the respondents' answers to $\mathrm{PRO}_1, \ldots, \mathrm{PRO}_4$. Further, we see that the answers to the probability questions are similar for the representative and high-income panel, whereas the

[8] The representative and the high income part of panel are combined.

stated possible incomes are higher for the high-income panel, as could be expected. This suggests that if we condition on income, we need not distinguish between the two parts of the panel.

Table 5.1 : Descriptive statistics for the answers to the quantitative questions for the representative and high-income part of the panel

	Lowest Income	Highest Income	PRO_1	PRO_2	PRO_3	PRO_4
Representative part of panel; 805 observations						
Minimum	3,000	5,000	0	0	0	0
1st Quartile	26,244	31,200	1	10	20	40
Median	40,000	45,000	10	25	50	70
3rd Quartile	54,000	60,000	25	50	75	90
Maximum	330,000	360,000	100	100	100	100
Mean	41,488	48,214	19.4	32.3	49.3	61.8
Std. Dev.	25,367	31,619	24.2	28.2	31.2	31.4
High-income part of panel; 322 observations						
Minimum	3,000	5,000	0	0	0	0
1st Quartile	40,000	55,000	0	10	20	40
Median	70,000	80,000	10	25	50	70
3rd Quartile	86,000	100,000	25	50	70	90
Maximum	300,000	800,000	100	100	100	100
Mean	64,363	77,547	17.3	29.6	46.0	61.4
Std. Dev.	39,910	61,788	23.3	26.8	31.5	32.3

Note: 205 respondents gave the same answer on the questions for the lowest and highest possible income. For these observations, the values for $PRO_1, \ldots, PRO_4$ are not determined, so they are not used in the last four columns.

In choosing a measure of income uncertainty, we will follow DM97. They use the interquartile range of the subjective distribution of next year's income as a measure of income uncertainty. To calculate this interquartile range, we specify a distribution function known up to a parameter (vector) θ and then estimate θ using our data (see also DM97). That is,

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \sum_{k=1}^{4} \left(\frac{\mathrm{PRO}_k}{100} - F(\mathrm{level}_k; \theta)\right)^2, \tag{5.1}$$

where $F(.;\theta)$ is a distribution function with unknown parameter θ. The parameter θ can then be estimated with Non-Linear Least Squares.

DM97 chose a lognormal distribution with a two-dimensional parameter vector θ: the median (to characterize the central tendency) and the interquartile range (to characterize its dispersion). Estimation is not possible 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.

DM97 compare their results with another study using survey data on future income expectations: a biennial survey of the Bank of Italy [the Survey of Household Income and Wealth (SHIW)]. The SHIW elicited points of 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.[9] Guiso et al. (1992) use the ratio of the standard deviation (σ) to the mean (μ) of the subjective real income distribution to measure subjective earnings uncertainty. Their results, the results of DM97, and our results based on the estimator in (5.1), are summarized in Table 5.2.

Table 5.2 (columns two, three and four) shows that the income uncertainty in the Netherlands, as measured by the coefficient of variation, is between the income uncertainty in Italy and the U.S.. This result suggests that Dutch households perceive more income uncertainty than Italian households do, but households in the U.S. face more income uncertainty than do households in the Netherlands. A χ^2-test has been used to test whether the difference in uncertainty between the U.S. and the Netherlands as tabulated in Table 5.2 is significant. The resulting test statistic is equal to 408, exceeding the critical value of 26.3. It should be mentioned 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 VSB panel are similar. In that respect, the U.S. and the Dutch results are comparable; it seems safe to conclude that perceived income uncertainty is smaller in the Netherlands than it is in the U.S..

[9] 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 and 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. In case 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).

Table 5.2 : Relative frequency distributions of the variation coefficient of future income

	Italian SHIW	U.S. SEE	Dutch VSB panel	Dutch VSB panel	Dutch VSB panel
			Lognormal	Beta	Interpol.
$\sigma/\mu = 0.000$	0.34	0.20	0.28	0.28	0.18
$\sigma/\mu \leq 0.005$	0.44	0.20	0.30	0.32	0.28
$\sigma/\mu \leq 0.015$	0.70	0.20	0.36	0.44	0.44
$\sigma/\mu \leq 0.025$	0.88	0.20	0.47	0.58	0.58
$\sigma/\mu \leq 0.035$	0.94	0.21	0.55	0.67	0.66
$\sigma/\mu \leq 0.045$	0.99	0.22	0.62	0.75	0.73
$\sigma/\mu \leq 0.065$	1.00	0.24	0.71	0.84	0.82
$\sigma/\mu \leq 0.100$	1.00	0.34	0.81	0.93	0.91
$\sigma/\mu \leq 0.150$	1.00	0.44	0.89	0.96	0.95
$\sigma/\mu \leq 0.200$	1.00	0.53	0.92	0.99	0.97
$\sigma/\mu \leq 0.300$	1.00	0.70	0.96	1.00	0.99
$\sigma/\mu \leq 0.400$	1.00	0.78	0.98	1.00	1.00
$\sigma/\mu \leq 0.500$	1.00	0.85	0.98	1.00	1.00
$\sigma/\mu \leq 1.000$	1.00	0.94	0.99	1.00	1.00
$\sigma/\mu \leq 2.000$	1.00	0.98	1.00	1.00	1.00
$\sigma/\mu \leq 5.000$	1.00	0.99	1.00	1.00	1.00
# obs.	2,909	437	982	982	1127

Note: For the Dutch VSB panel, the estimation procedure for the unknown parameter vector in case of the lognormal and Beta 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.

A disadvantage of using the lognormal distribution is the fact that we do not use explicitly the information on the reported lowest and highest possible income. The lognormal distribution also takes values outside the interval [lowest possible income, highest possible income]. In our case, a substantial part of the total probability mass is outside the interval. To give an indication, 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 to 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.

We can explicitly use the information on the reported lowest and highest possible incomes by putting all the probability mass on the reported interval. A possible distribution that takes this into account is the Beta distribution. This family of distributions is flexible in that it covers both symmetric and asymmetric distributions.

The effect of estimating a distribution function defined on the reported interval becomes clearer when we look at the fifth column of Table 5.2. This column displays the variation coefficient of future income in the Netherlands when we use estimates derived from a Beta distribution. We see that the relative frequencies in the Dutch case come closer to the Italian numbers.

When estimating the lognormal or Beta distribution, we cannot use the observations where the respondent gave the same answer to all $PRO_1, \ldots, PRO_4$. This means a loss of 145 observations. But all these respondents gave a useful answer to the lowest and highest possible income and therefore provided useful information on their subjective income uncertainty. If we assume that the density of the subjective income distribution is simply (piecewise) uniform over the intervals, we are able to use these observations. In this case, we can obtain the estimated cumulative distribution function by interpolation between the known points 0, $PRO_1, \ldots, PRO_4$, and 100. The relative frequency distribution of the variation coefficient in case of the interpolated distribution is presented in the sixth column of Table 5.2. Only for small values of the variation coefficient do we find differences with column 5. The characteristics such as median or interquartile range are similar in case of interpolation compared to the estimated Beta distribution. In all further analyses we will use the characteristics of the piecewise uniform distribution function.

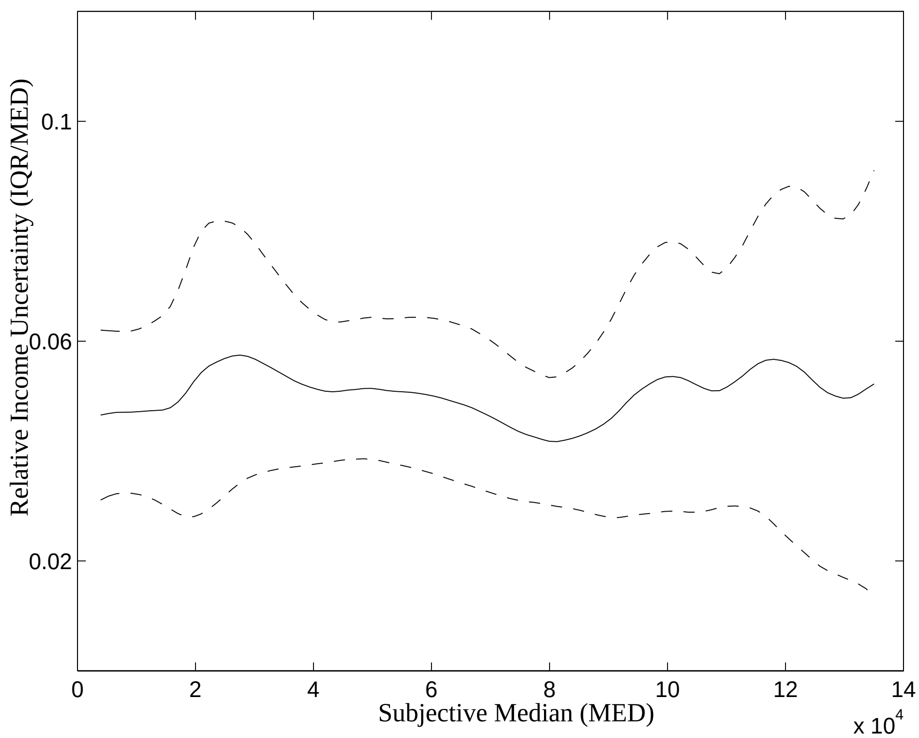
The rank correlation between IQR and MED is 0.43 and highly significant. It would be interesting to know what the relationship is between the expected level of income and subjective income uncertainty. In the case where IQR is proportional to MED, the relative income uncertainty (IQR/MED) is constant. Using our data, we (nonparametrically) regress the quotient IQR/MED on MED. The result is presented in Figure 5.1. Together with the estimated functional relationship between IQR/MED and MED, we present 95% uniform confidence bounds. [10]

Figure 5.1 shows that the median of the subjective income distribution has no significant effect on relative income uncertainty as perceived by the head of household. This implies that households that expect a higher income next year do not perceive a greater or smaller *relative* uncertainty than others do. In studies by Skinner (1988),

[10] We use the quartic kernel and a bandwidth equal to $1,5 \times 10^4$. For details on nonparametric regression, see e.g. Härdle and Linton (1994).

Zeldes (1989), and Carroll (1992), the household's subjective IQR is also proportional to the median. However, these studies rely on realizations and on a log-normality assumption,[11] while our conclusion is based on survey data on subjective income expectations.

Figure 5.1 : Nonparametric regression of relative subjective income uncertainty (IQR/MED) on the subjective median of future income (MED). The dashed lines are 95% uniform confidence bands.



Qualitative versus Quantitative measurement

As we already mentioned in Section 5.2.1, we also have some qualitative questions related to the expectations on household income in the next twelve months. These questions are related to changes in household income in relation to income in the past twelve months (for the precise formulation of the questions, see Appendix 5.A).

[11]Carroll (1992) superimposes a 0.005 chance of receiving no income at all. As already mentioned by DM97, this slight modification of the log-normality assumption has a negligible effect on the median and IQR of the subjective income distribution.

We constructed probabilities for the categories of income changes by assigning weights to the different answering categories. Since for a given question a higher category corresponds to a higher likelihood, we assign increasing weights to the categories for each question. A general way to do this would be as follows:

$$W_j = \alpha_j + \beta_j * \text{number}_j, \text{ with}$$
$$j = 1 \text{ (Increase of more than 15\%)}, \ldots, 7 \text{ (Decrease of more than 15\%)}.$$

Here W_j is the weight assigned to the income change for category j if number_j was the number for the answer category for income change j, with number_j in {1(*highly unlikely*),...,7(*highly likely*)}. The reason the weights are modelled this way is mainly because the probability related to *highly likely* does not necessarily have to be equal to 7 times the probability of *highly unlikely*. Since there are no verbal clarifications for the answers between the extremes 1 (*highly unlikely*) and 7 (*highly likely*), we see no reason why we should not assume equal increases for the probabilities corresponding to the answer within the range *highly unlikely*, ..., *highly likely*. All we know is that $\beta_j > 0$ and $\alpha_j + \beta_j \geq 0$.

To obtain probabilities from these weights, we simply normalized them to sum to one, that is

$$P_j = \frac{W_j}{\sum_{k=1}^{7} W_k}.$$

Adding these probabilities yields six points on the cumulative distribution function for the expected income changes. We can derive a median change and the interquartile range of income changes by interpolation between the known points of the cumulative distribution function, similar to the procedure used for the quantitative data.

We want to compare the measure of uncertainty obtained from the qualitative questions with the measure obtained from the quantitative questions. The problem, however, is that the quantitative questions refer to income levels, while the qualitative questions refer to percentage changes from past income. Since we have information on only income classes for the past twelve months' income, we will obtain imprecise results if we use this variable to scale the distribution for income changes to a distribution for expected income levels. When we calculate the ratio of the interquartile range to the median, however, the scale drops out and we obtain the same expression as for the quantitative information.[12] To see whether the qualitative data yields similar

[12] To be exactly, $\frac{IQR_t(y_{t+1})}{MED_t(y_{t+1})} = \frac{IQR_t(\Delta y_{t+1}/y_t)}{MED_t(\Delta y_{t+1}/y_t)+1}$.

outcomes as compared with those of the quantitative data, we examine the correlation between the ratio of the interquartile range to the median for the two types of data. The rank correlation coefficient is equal to 0.25 and is highly significant.

5.4 Prediction of the subjective measure of income uncertainty.

This section examines how our measure of income uncertainty varies with some household characteristics. A (possible) correlation can yield useful information. First, 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. Second, if a relationship exists, this information might be useful for studies in which no subjective data are available. In that respect, we try to gain some insight into the way the employment status of the partner affects the income uncertainty of the household.

Before we discuss the results for income uncertainty, we will examine the location of the subjective income distribution.

Location

We estimate a simple model for the median of the subjective income distribution (as a measure of location): the same linear specification as 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. Appendix 5.B presents the exact definitions of the explanatory variables and Appendix 5.C provides some descriptive statistics. 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 5.3 presents the estimation results.

The first column in Table 5.3 shows that the household income in the past twelve months is a dominant predictor for the expected household income in the next twelve months. A striking result is that the estimated coefficient is almost the same as that found by DM97. The best linear prediction of the location measure of the subjective income distribution increases 834 Dutch guilders with every one thousand Dfl. increase of past household income.

Table 5.3 : Estimation results for the median

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)
$\text{Age}^2/100$	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	

Note: Standard errors are in parentheses.

Heads of households with a higher level of education expect a higher level of income in the next twelve months. However, the joint hypothesis about whether all dummy variables corresponding to the level of education are equal to zero cannot be rejected (significance probability of 0.40).

The first column of Table 5.3 shows also that differences exist between heads of households and partners in the effect of labor-market status 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 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 the head of household and partner. The resulting estimates are presented in the second column of Table 5.3. When we consider a household with a working head and a non-working partner, the coefficient on household income is equal to 0.914. For a household with a working head and working partner, this coefficient is equal to 0.799. This suggests that last year's household income is less dominant in predicting next year's household income when the partner is working. Note that these results are conditional on whether or not the head expects some household member to stop working. This expectation exerts a strong negative effect. The effect of a member in the household who is expected to start working is smaller and insignificant.

The above explanation for the smaller part of last year's household income which is carried over into expectations for the next year also suggests that a household with working head and partner faces more income uncertainty than does a household with working head and non-working partner. This issue will be addressed when we move on to income uncertainty.

Absolute income uncertainty

As mentioned before, we use the InterQuartile Range (IQR) as a measure for income uncertainty. The IQR is a measure for absolute income uncertainty (that is, a guilder more is the same for all households, independent of the level of their income). The end of this section will also address relative income uncertainty.

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 some variables referring to expectations about income changes in the past and future. The variable PrevΔInc denotes the subjective change in household income in 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 appear in Table 5.4.

Table 5.4 : Estimation results for the interquartile range

DEPENDENT VARIABLE: IQR (in hundreds of Dfl.)				
	without income change variables		with income change variables	
Constant	47.7	(5.5)	35.5	(10.0)
PastInc	0.123	(0.016)	0.116	(0.042)
DumWork	-1.65	(0.96)	3.42	(1.6)
DumWorkP	2.80	(1.2)	-0.922	(1.8)
DumUnem	0.992	(1.1)	0.879	(2.9)
DumUnemP	11.9	(1.3)	11.5	(2.3)
DumFemale	-2.56	(1.2)	-2.14	(1.2)
DumPartner	-1.30	(1.2)	-0.870	(1.2)
Age/10	-15.1	(2.1)	-11.9	(3.3)
$\mathrm{Age}^2/100$	1.15	(0.21)	0.925	(0.28)
DumEdu2	0.570	(2.0)	1.01	(0.91)
DumEdu3	1.06	(1.9)	1.33	(1.3)
DumEdu4	-0.745	(1.9)	-0.389	(0.95)
DumEdu5	0.905	(2.0)	1.20	(1.7)
PrevΔInc			0.0661	(0.17)
$\lvert$PrevΔInc$\rvert$			0.125	(0.16)
ExpΔInc			0.105	(0.14)
$\lvert$ExpΔInc$\rvert$			0.373	(0.18)
Average Abs. Dev.	2.42		2.40	

Note: Standard errors are in parentheses.

The first column of Table 5.4 shows that the IQR depends significantly on income in the last twelve months, but the effect is small if we compare it with the results obtained by DM97 for the U.S.. The difference in magnitude is more than tenfold (and confidence intervals do not overlap). This is, of course, related to the earlier finding that heads of American households perceive far more income uncertainty than do their counterparts in Dutch households.

Furthermore, we find, unlike DM97, a positive effect of a working partner on income uncertainty. Income uncertainty is even higher when the partner is unemployed and searching for a job. A female head of household perceives less income uncertainty than does a male head, as is shown by the coefficient corresponding to DumFemale being significantly negative.

We included a quadratic age pattern. The estimated coefficients are highly significant. Absolute income uncertainty decreases with age until the age of retirement.

Although DM97 don't include a quadratic term, they also find a negative relationship between income uncertainty (as measured by IQR) and age. The education level has no effect, as is shown by a joint test on the coefficients for the dummy variables (significance probability of 0.62).

The second column of Table 5.4 shows the estimation results after we included expectations and perceived realizations of income changes. It turns out that only the absolute value of the expected income change (ExpΔInc) has a significant influence on income uncertainty: the larger the expected change, the more uncertain a head of household is about future income. We included both the expected income change and its absolute value to see whether an expected increase in household income has a different effect than an expected decrease in household income. This, however, makes no difference. Past income changes have no significant effect.

Relative income uncertainty

The IQR is a measure of income uncertainty that does not take into account the level of income at which the variation in income takes place. This section will examine a measure of relative uncertainty of next year's income by taking the ratio of IQR to MED as our variable of interest. This measure looks at income changes as relative deviations from the median. Estimation results are presented in Table 5.5.

Results in the first column of Table 5.5 reveal that household income in 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 5.1). 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%.[13]

When we look at the labor-market status variables for head and partner, we see that if a partner has a job, this does not influence relative income uncertainty, whereas the fact that the head of household has a job increases relative income uncertainty by almost one percentage point. The unemployment dummies for head and partner are of the same order of magnitude. (Note, however, that DumUnemP is significant and DumUnem is insignificant.) A test on the joint significance of the dummy variables corresponding to the level of education indicates that there exist differences between

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

education levels (the significance probability is equal to 0.03).

Table 5.5 : Estimation results for relative income uncertainty

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)
$Age^2/100$	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)
PrevΔInc			0.0222	(0.040)
$\vert$PrevΔInc$\vert$			0.0321	(0.035)
ExpΔInc			0.0595	(0.047)
$\vert$ExpΔInc$\vert$			0.0984	(0.035)
Average Abs. Dev.	4.09		4.04	

Note: Standard errors are in parentheses.

When we include some characteristics of past and expected income changes, we obtain the results presented in the second column of Table 5.5. Again we see that only the absolute magnitude of expected income changes influences income uncertainty in a positive way. The effects of the other variables are the same as in the first column. Only the variable DumWork is no longer significant.

Comparing the estimation results in Table 5.4 and Table 5.5, we see that the signs of all the significant variables are the same. The age pattern has not changed much: income uncertainty decreases until the age of retirement. The level of education, however, influences relative income uncertainty significantly, while it does not affect absolute income uncertainty. Finally, it should be noted that comparing the magnitude of the effects makes no sense, since we try to explain a different measure of income uncertainty (*absolute* versus *relative*).

5.5 Conclusions

We have analyzed subjective data on income uncertainty using data from the 1995 wave of the Dutch VSB panel. In the analysis, we use questions that elicit the subjective income distribution in a quantitative way. We compare our measure of income uncertainty with corresponding studies conducted in the U.S. and Italy and find that perceived income uncertainty in the U.S. is larger than it is in the two European countries.

There was also a significant correlation between two different measures of income uncertainty, one measure being derived from qualitative questions, the other from questions with quantitative answers.

The median of the subjective income distribution is used as a measure of the household's income level. We find that the household income in the past twelve months is a dominant predictor for future income. However, last year's household income is less dominant in predicting next year's household income when the partner is working.

We use as a measure of future income uncertainty the interquartile range of the subjective income distribution. We distinguish between absolute and relative income uncertainty. For both measures we find that income uncertainty decreases with age until retirement. Furthermore, there is a positive effect of a working partner on income uncertainty. This effect increases when a partner is unemployed and searching for a job.

Results from our analysis suggest that it is worthwhile to use subjective data; it 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.

5.A Appendix: exact wording of survey questions

"Income" part of questionnaire

On the next screen you will be asked how much, approximately, the TOTAL NET INCOME OF YOUR HOUSEHOLD AS A WHOLE has been over the period 1 January 1994 through 31 December 1994. The total net income of the household means the sum of net incomes of all household members. By net income we mean the income after deduction of taxes, but before making payments for things like rent, mortgages, and the like.

Please indicate about how much the TOTAL NET INCOME OF YOUR HOUSEHOLD was over the period 1 January 1994 through 31 December 1994.
Possible answers: Less than Dfl. 17,500 (1); Dfl. 17,500 - Dfl. 20,000 (2); Dfl. 20,000 - Dfl. 24,000 (3); Dfl. 24,000 - Dfl. 28,000 (4); Dfl. 28,000 - Dfl. 34,000 (5); Dfl. 34,000 - Dfl. 43,000 (6); Dfl. 43,000 - Dfl. 55,000 (7); Dfl. 55,000 - Dfl. 80,000 (8); Dfl. 80,000 - Dfl. 105,000 (9); Dfl. 105,000 - Dfl. 150,000 (10); Dfl. 150,000 or more (11); (Also a *Don't know* category is given.)

We would like to know a bit more about your expectations of total net household income in the next 12 months. What do you think is the LOWEST amount that your total net household income could possibly be over the next 12 months?

The same question is asked for HIGHEST amount of total net household income.

Next we will show you a number of possible amounts of total net household income. Can you indicate for each of these amounts what the probability in percentages is (or number of cases out of 100) that the total net household income in the next 12 months will be LESS than the given amount?

What do you think is the probability that the total net household income in the next 12 months will be less than *[LOWEST + (HIGHEST - LOWEST)*0.2]* ?[14]
Fill in a number between 0 and 100.

This question is repeated for *[LOWEST + (HIGHEST - LOWEST)*0.4]*, *[LOWEST + (HIGHEST - LOWEST)*0.6]*, and *[LOWEST + (HIGHEST - LOWEST)*0.8]*.

[14] Automatically filled in by the computer.

"Economic and psychological concepts" part of questionnaire

The TOTAL NET INCOME OF YOUR HOUSEHOLD consists of the income of all members of the household, after deduction of taxes, taken as the sum total over the past 12 months.

PREVIOUS INCOME CHANGE:
Compared to about one year ago, did the total net income of your household increase, remain about the same, or decrease?
Possible answers: increase (1), remain about the same (2), and decrease (3).

Only for those who filled in a change: By what PERCENTAGE (approximately) has the total net income of your household increased (decreased)?
(Note: for those who filled in *remain about the same* the income change is set to 0% in the analysis.)

FUTURE INCOME CHANGE:
Do you think, taking into account possible changes within the household, the total net income of your household will increase, remain the same, or decrease IN THE NEXT 12 MONTHS? *Possible answers: increase (1), remain about the same (2), and decrease (3).*

Only for those who filled in a change: By what PERCENTAGE do you think the total net income of your household will increase (decrease) IN THE NEXT 12 MONTHS?
(Note: for those who filled in *remain about the same* the income change is set to 0% in the analysis.)

We would like to know a bit more about your expectations of the next 12 months. Below we have presented a number of possible changes in income. Please indicate (on the scale given) with any of those changes, how likely you think it is that the total income of your household will change by that percentage IN THE NEXT 12 MONTHS.

A rise in income of more than 15%
Possible answers: Highly unlikely (1), (2), (3), (4), (5), (6), and Highly likely (7).
Note that only the endpoints (1) and (7) have a verbal explanation. Also a category *Don't know* is given.

The above question is repeated for a rise in income between 10 and 15%, a rise in income between 5 and 10%, no significant change in income (change not more than 5%), a drop in income between 5 and 10%, a drop in income between 10 and 15%, and a drop in income of more than 15%.

5.B Appendix: reference list variables

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 (see Appendix A). The variable is measured in thousands of Dutch guilders.

DumWork Dummy variable: 1 if the head of household has a paid job, 0 otherwise.

DumWorkP Dummy variable: 1 if the partner has a paid job, 0 otherwise.

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, 0 otherwise.

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.

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 any one member of the household who is currently not employed will start working, 0 otherwise.

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 any one member of the household who is currently employed will stop working, 0 otherwise.

PrevΔInc	Previous change in income in the past twelve months. The variable is measured in percentage terms (see Appendix 5.A).
ExpΔInc	Expected change in income in the next twelve months. The variable is measured in percentage terms (see Appendix 5.A).

5.C Appendix: descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.
MED	52,514	34,609	3,933	342,000
IQR	2,838	6,222	0	128,000
IQR/MED	0.0515	0.0793	0	0.895
PastInc	62.5	31.1	15	175
DumWork	0.717	0.451	0	1
DumWorkP	0.382	0.486	0	1
DumUnem	0.161	0.367	0	1
DumUnemP	0.0967	0.296	0	1
DumFemale	0.137	0.344	0	1
DumPartner	0.800	0.400	0	1
Age	49.0	13.2	22	88
DumEdu1	0.0481	0.214	0	1
DumEdu2	0.183	0.386	0	1
DumEdu3	0.268	0.443	0	1
DumEdu4	0.305	0.460	0	1
DumEdu5	0.197	0.398	0	1
DumStartW	0.0258	0.158	0	1
DumStopW	0.0506	0.219	0	1
PrevΔInc	0.399	8.06	-80	100
$\vert$PrevΔInc$\vert$	2.98	7.50	0	100
ExpΔInc	-0.239	8.78	-40	100
$\vert$ExpΔInc$\vert$	3.03	8.24	0	100

Chapter 6

Extensions of the Ordered Response Model

In an ordered response model, the observed variable is based upon classifying an unobserved variable into one out of a finite number of intervals forming a dissection of the real line (cf. Amemiya, 1981). This model considers the thresholds of the intervals as (unknown) deterministic parameters, the same for every individual. Terza (1985) extends this through the relaxation of the assumed constancy of the thresholds: he allows the thresholds to be a linear function of observed explanatory variables. We extend the deterministic model by allowing for random thresholds that vary across individuals. A case study on consumer valuation of new products indicates that random thresholds significantly improve the standard ordered response model.

6.1 Introduction

In his survey article, Amemiya (1981) describes the ordered response model in which the dependent variable can take more than two discrete values. Econometric examples of these ordered multi-response models can be found in Silberman and Talley (1974, bank chartering) or David and Legg (1975, demand for housing). More recent applications are opinions about job satisfaction (Clark, 1993) or satisfaction with life or income (Melenberg and Van Soest, 1994, 1995). Chapters 2 and 3 use the ordered multi-response model to explain income growth expectations.

To characterize the responses of the discrete dependent variable y, one constructs an unobservable continuous random variable y^*. The variable y is then based upon classifying the unobserved y^* into one out of a finite number of intervals forming a dissection of the real line. In the standard model, the thresholds of the intervals are considered to be unknown constants with the interpretation that the partition of the real line does not vary across individuals. This seems to be unrealistic. Terza (1985) relaxes the assumption of constant thresholds. He assumes that the thresholds of the intervals are a linear function of known explanatory variables. When a (linear) relationship is indeed found, the thresholds are observation specific.

As Terza does, we also assume that every individual may have a different dissection of the real line. This dissection is known by the individual but cannot be observed by the researcher. Without assuming a functional form between thresholds and known explanatory variables, we proceed as follows. If we draw a random sample from a population of individuals, then we also have a random sample from a "population of thresholds," since the individual specific thresholds are unobserved by the researcher. This means that we replace the deterministic thresholds by random thresholds. The unobserved y^* will then be classified according to a random dissection of the real line.

In Chapter 2 the thresholds are assumed to be constant across individuals. This is also the case for the random effects specification in the panel data model described in Chapter 3. For the fixed effect specification, however, the thresholds are allowed to be individual specific, since the minimum sufficient statistic for α_i is also a minimum sufficient statistic for the threshold parameter. Therefore, this parameter drops from the conditional likelihood function and can freely vary among individuals. In that case, the thresholds are not estimated and are seen as nuisance parameters. This chapter concentrates on (explicitly) modeling individual specific thresholds.

The outline is as follows. Section 6.2 briefly describes the standard ordered response model. Section 6.3 discusses two extensions of the standard ordered response model. First we describe the extension proposed by Terza. Second we propose an extension to random thresholds. This extension of the standard ordered response model is the main focus of this chapter. Section 6.4 applies the two extensions to a data set focusing on consumer valuation of three new products (on a seven-point scale). Although the application has limited economic relevance, it serves perfectly as an illustration of the extension of the standard ordered response model. The empirical application indicates that the random thresholds significantly improve the model, while Terza's linear relationship might be too restrictive to explain individual specific thresholds. Section 6.5 concludes.

6.2 The basic framework

In the (univariate) ordered response model, the discrete dependent variable y_i of individual i is based upon an unobserved continuous variable $y_i^* \in \mathbb{R}$. Assume that y_i^* can be modelled as

$$y_i^* = x_i'\beta + \varepsilon_i, \qquad i = 1, \ldots, n$$

where n is the number of individuals, $x_i \in \mathbb{R}^k$ is a vector of k explanatory variables, $\beta \in \mathbb{R}^k$ is a vector of unknown parameters and ε_i is a disturbance term with distribution not depending on x_i. Furthermore, we assume that the disturbance terms are i.i.d. with zero mean and scale parameter σ: $\varepsilon_i/\sigma \sim F$, $i = 1, \ldots, n$ (e.g. F is the standard normal cdf.). The dependent variable y_i takes p values $1, ..., p$ corresponding to a partition of the real line into p parts using $p+1$ thresholds $m_0 \equiv -\infty < m_1 < \ldots < m_{p-1} < m_p \equiv \infty$:

$$y_i = j \text{ if } m_{j-1} \leq y_i^* < m_j, \qquad j = 1, \ldots, p. \tag{6.1}$$

In this basic model, the thresholds $m_1, \ldots, m_{p-1}$ are considered as deterministic but unknown. For identification in this model, location and scale must be fixed. This can be done by fixing m_1 and m_{p-1}. Another possibility is to fix m_1 and σ. The first procedure is preferable, since this leads to a more natural interpretation of the parameter estimates. In applications (like the one in Section 6.4), y^* will be considered as some continuous analog of y. An obvious choice would then be $m_1 \equiv 1\frac{1}{2}$ and $m_{p-1} \equiv p - \frac{1}{2}$.

The most common way of estimating model (6.1) is by maximum likelihood. Define

$$y_{ij} \equiv \begin{cases} 1 & \text{if } y_i = j, \\ 0 & \text{if } y_i \neq j, \end{cases}$$

with $i = 1, \ldots, n$ and $j = 1, \ldots, p$ and $P_{ij} \equiv P(y_i = j)$. The likelihood function (LF) can then be written as

$$LF = \prod_{i=1}^{n} \prod_{j=1}^{p} P_{ij}^{y_{ij}}.$$

It is common to work with the logarithm of LF, which will be denoted by LLF.

6.3 Extensions

This section discusses two extensions of the basic ordered response model introduced in the previous section. The emphasis will be on the interpretation of the model. The extensions entail the elimination of the assumption of constant thresholds. It is not realistic to assume that individuals base their opinions on the same dissection of the real line. Besides the better interpretation of the model, it is interesting whether this relaxation of the assumption of constant thresholds leads to a better fit.

First comes a brief discussion of the extension proposed by Terza (1985). He assumes that the thresholds are a linear function of known explanatory variables. Next follows our extension to random thresholds.

6.3.1 Terza's extension

Terza (1985) extends the conventional probit model described in McKelvey and Zavoina (1975) to analyze ordinal qualitative variables. He assumes that the thresholds $m_1, \ldots, m_{p-1}$ can be written as a linear function of an observed vector of deterministic variables, Z_i. This results in writing the thresholds with a subindex i: $m_{i,j}$. The relationship is then given by

$$m_{i,j} = Z_i' \alpha_j,$$

where $\alpha_1, \ldots, \alpha_{p-1}$ are the unknown parameter vectors to be estimated. As mentioned by Terza, unconstrained maximization of the loglikelihood function may violate the ordering in the thresholds. The range of the $\alpha_j' s$ should be such that $Z_i' \alpha_{j-1} \leq Z_i' \alpha_j$ holds for every i and j, which implies that $m_{i,j-1} \leq m_{i,j}$. If this condition is violated, the likelihood function should be maximized subject to the inequality constraints.

We also assume that the thresholds are not constant, but vary across observations. The idea of having different dissections of the real line will be applied in another way.

6.3.2 Random thresholds

This subsection extends the standard ordered response model with the assumption that the individuals classify their scores into a self-chosen dissection of the real line. We do not assume a functional relationship between thresholds and known explanatory variables (as Terza does). We start in this subsection with the univariate case and then move on to the multivariate case.

Univariate case

Assume that every individual has a specific array of thresholds of the intervals. Individuals know these thresholds, and according to this known dissection of the real line they classify their scores. However, the individual-specific thresholds cannot be observed by the researcher. A random sample from a population of individuals will therefore imply a random sample from a population of thresholds. This random individual effect in the thresholds means that instead of considering deterministic thresholds, we consider random thresholds: $m_{i(1)} < \ldots < m_{i(p-1)}$ are assumed to be distributed according to some distribution not depending on the x_i. Furthermore, we assume that the ε_i and $\{m_{i(1)}, \ldots, m_{i(p-1)}\}$ are independent.

A simple way of specifying the distribution of $\{m_{i(1)}, \ldots, m_{i(p-1)}\}$ is to identify it with the distribution of order statistics:

> $m_{i(1)}, \ldots, m_{i(p-1)}$ are the order statistics of mutually independent (auxiliary) $m_{i,1}, \ldots, m_{i,p-1}$ and the distributions of $m_{i,j}$ only differ with location:
>
> $$m_{i,j} - \theta_j \sim D(\Delta) \quad (j = 1, \ldots, p-1) \tag{6.2}$$
>
> with unknown deterministic Δ and $\theta_1 < \ldots < \theta_{p-1}$.

For likelihood calculations, we may assume without loss of generality that the ε_i and $\{m_{i,1}, \ldots, m_{i,p-1}\}$ are independent.

Defining $m_{i(0)} \equiv -\infty$ and $m_{i(p)} \equiv \infty$ (deterministic), model (6.1) becomes

$$\begin{aligned} y_i^* &= x_i'\beta + \varepsilon_i, \\ y_i &= j \text{ if } m_{i(j-1)} \leq y_i^* < m_{i(j)}, \quad j = 1, \ldots, p. \end{aligned} \tag{6.3}$$

Although models (6.3) and (6.1) resemble each other, the likelihood function is more difficult to calculate in the case of (6.3) (the likelihood contributions are given in Appendix 6.A). This will certainly be true when we extend the univariate case to the multivariate case.

Multivariate case

This section briefly discusses the extension to the multivariate case. Empirical examples in which the dependent variable is multivariate are valuations or opinions about more than one subject (see the application in Section 6.4).

The extension of the univariate case (6.3) to the multivariate case is straightforward. We make only some additional assumptions. Every individual gives a valuation or opinion about l subjects or issues: $y_i \in \mathbb{R}^l$. Assume that the subjects are comparable. Thus, it is reasonable to assume that, for each individual, the thresholds do not vary with l. Then the multivariate extended ordered response model for individual i can then be written as

$$\begin{aligned} y^*_{i,h} &= x'_{i,h}\beta_h + \varepsilon_{i,h}, \\ y_{i,h} &= j \text{ if } m_{i(j-1)} \leq y^*_{i,h} < m_{i(j)}, \end{aligned} \tag{6.4}$$

with $h = 1, \ldots, l$ and $j = 1, \ldots p$. The error terms $\varepsilon_i = (\varepsilon_{i,1}, \ldots, \varepsilon_{i,l})' \in \mathbb{R}^l$ are assumed to be i.i.d. with zero mean: $\Sigma^{-\frac{1}{2}}\varepsilon_i \sim F_l$, where

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdot & \sigma_{1l} \\ \cdot & \sigma_2^2 & \cdot & \sigma_{2l} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \sigma_l^2 \end{bmatrix}$$

is a positive definite matrix and F_l is an l-dimensional distribution. The off-diagonal elements in the matrix Σ may be different from zero, so some correlation is allowed between ε_{ih} and ε_{ig}. Individuals who are likely to give high scores will do this for each valuation. Further, the error terms corresponding to different valuated subjects may have different variances. We come back to this in Section 6.4.2.

Contrary to the univariate case, calculating the likelihood function is rather complex in the multivariate case, particularly for a relatively large p. We therefore consider a rather special case of (6.2). Assume that $\mathcal{R}(D) = [-\Delta, \Delta]$, with $0 \leq \Delta \leq \frac{1}{2}\min(\theta_j - \theta_{j-1}, j = 2, \ldots, p-1)$. This means that $m_{i,1} = m_{i(1)}, \ldots, m_{i,p-1} = m_{i(p-1)}$. If $\Delta = 0$, the model with random thresholds reduces to the model with deterministic thresholds.

6.4 Application to valuation of new products

This section applies the ordered response model with its extensions introduced in the previous section. The application concerns consumer valuations of new products. New products are crucial to successful growth, but their introduction is risky (Urban and Hauser, 1993). Firms must therefore understand how different compositions of a new product will be valuated before the final product is put on the market. This can be done with the use of (subjective) answers to questions on product evaluation. Although it is not our objective to go into detail about our specific application, we estimate several models to see whether the introduction of random thresholds gives a better fit.

Section 6.4.1 will describe the experimental design and the data used in this application. Estimation results appear in Section 6.4.2 and Section 6.4.3 examines different product characteristics.

6.4.1 Experimental design and data

The data are taken from a research project from MARS (Veghel, the Netherlands). MARS investigated the opinion on three new compositions of the candy-bar *TWIX*, henceforth coded as T1, T2 and T3. Individuals were asked to give their opinion about two of the three compositions. [1] The order in which the questions were asked might be of significance.

Every family member aged nine years or older filled in a questionnaire. The total number n of individuals used in the sample equals 853. The valuation of the first product tasted by individual i will be denoted by $y_{i,1}$ and the second valuation will be denoted by $y_{i,2}$. Individuals gave their valuations on a seven-point scale ranging from very bad (1) to very good (7). Table 6.B.1 in Appendix 6.B provides the number of observations in each cell. Note that the number of observations corresponding to low valuations is very small. This can hinder the performance of the ML-estimator based on asymptotic properties. Therefore we combine several cells: the values 1,2 and 3 are redefined as 3. The discrete dependent variables $y_{i,1}$ and $y_{i,2}$ can thus take the values $3, 4, 5, 6$ and 7.

Information is available about the following variables:

dumT1	: 1 if valuation is related to product T1; 0 otherwise,
dumT2	: 1 if valuation is related to product T2; 0 otherwise,
dumT3	: 1 if valuation is related to product T3; 0 otherwise,
age/10	: age (in tens of years),
sex	: 1 = male, 2 = female,
fam size	: family size,

[1] Psychologists advising MARS argue that it is ill-advised to let one individual taste more than two products. This leads to unreliable answers. Therefore individuals taste only two of the three products. The researcher decides (randomly) which two products will be tasted by a particular individual.

ch $<$ 15	: number of children younger than 15 living at home,
chocolate	: opinion about chocolate taste,
	1 = very bad, ..., 5 = very good,
caramel	: opinion about caramel taste (see chocolate),
biscuit	: opinion about biscuit taste (see chocolate).

Some summary statistics can be found in Table 6.B.2 in Appendix 6.B. Results reveal hardly any difference between the mean valuation of the different product characteristics (chocolate, caramel and biscuit taste) with respect to the compositions T1, T2 and T3. Since larger families (fam size) and in particular a larger number of young children (ch $<$ 15) can influence the appetite for the product (interdependency), these variables are also taken into account.

A significant order effect would result in an obvious difference between the estimated parameters corresponding to the first and second evaluation. Because in neither of the estimated models did an LR-test reject the hypothesis $\beta_1 = \beta_2$, we assume (for simplicity) $\beta_1 = \beta_2 = \beta$.

6.4.2 Estimation results

This section presents the estimation results. First we will estimate the standard model with constant thresholds and the extended model in which the thresholds are a linear function of some individual characteristics (Section 6.3.1). All the estimated models are based on (6.4) with $l = 2$ and F is the two-dimensional standard normal distribution. We write $\rho = \sigma_{12}/\sigma_1\sigma_2$. The results are summarized in Table 6.1.

Examination of the coefficients corresponding to the exogenous variables in the linear specification for the thresholds, reveals that no parameter is significantly different from zero except the constant terms. A (joint) LR test cannot reject the hypothesis of having constant thresholds ($6.74 < \chi^2_{6:0.05} = 12.59$).

Section 6.4.1 stated that there was no order-effect, in the sense that $\beta_1 = \beta_2$ is not rejected. On the other hand, a difference does exist between the variances of the two opinions: σ_2 is (significantly) larger than σ_1. After evaluating the first tasted product, individuals seem to have some *standard measure*. Based on this *standard measure*, they could provide more extreme valuations for the second tasted product.

With regard to other parameter estimates in the standard model (1), note that *sex*, *fam size* and *ch* $<$ 15 are not significantly different from 0. On the other hand, the variables *age*/10 and (*age*/10)^2 are significantly different from 0. The negative coefficient corresponding to *age*/10, together with the positive coefficient of *(age/*10*)*^{2}, implies (*ceteris paribus*) a U-shaped relation between *age* and the valuation – with a minimum at 41 years of age. The relatively younger and older people prefer the product more than middle-aged individuals do.

Table 6.1 deterministic thresholds
(standard errors in parentheses)

	(1) Standard model		**(2)** Terza's extension	
parameter	estimate		estimate	
constant*	1.99	(0.22)	2.13	(0.23)
dumT1	-0.0720	(0.039)	-0.0717	(0.040)
dumT2	-0.0645	(0.039)	-0.0635	(0.039)
age/10	-0.290	(0.067)	-0.328	(0.088)
(age/10)^2	0.0350	(0.010)	0.0385	(0.014)
sex	0.0752	(0.051)	0.0376	(0.068)
fam size	0.0419	(0.029)	0.0431	(0.029)
ch < 15	0.0222	(0.026)	0.0211	(0.026)
chocolate	0.540	(0.030)	0.538	(0.030)
caramel	0.313	(0.026)	0.314	(0.026)
biscuit	0.147	(0.027)	0.145	(0.027)
m_1	3.5		3.5	
m_2	4.33	(0.046)		
α_{21}: constant			4.34	(0.192)
α_{22}: age/10			0.0346	(0.109)
α_{23}: (age/10)^2			-0.00421	(0.017)
α_{24}: sex			-0.0497	(0.075)
m_3	5.19	(0.037)		
α_{31}: constant			5.47	(0.159)
α_{32}: age/10			-0.105	(0.092)
α_{33}: (age/10)^2			0.0106	(0.014)
α_{34}: sex			-0.0615	(0.070)
m_4	6.5		6.5	
σ_1	0.709	(0.026)	0.703	(0.027)
σ_2	0.799	(0.026)	0.798	(0.027)
ρ	0.642	(0.023)	0.639	(0.023)
LLF	-1680.3		-1676.9	

* We included a constant term, dumT1 and dumT2 instead of the three dummies. The remaining two dummies can then be interpreted as differences between T1 and T3, and T2 and T3.

The coefficients with respect to *chocolate*, *caramel* and *biscuit* taste are (as would be expected) positive: the better some product characteristics are valuated, the better the overall product is valuated. The ordering in the parameter estimates corresponding to the product characteristics means that chocolate taste is the most important characteristic in determining the overall opinion about the product. However, these coefficients do not tell anything about the final composition of the product. The next section further analyzes the chocolate, caramel and biscuit taste.

Now consider our alternative model extension – a model with random thresholds. Again the estimated models are based on (6.4), with $l = 2$ and F is the two-dimensional standard normal distribution. Let

$$m_{i,j} - \theta_j \overset{\mathcal{L}}{=} 2\Delta\, w - \Delta \tag{6.5}$$

with $w \sim \text{Beta}(p, q)$. [So $D(\Delta)$ in (6.2) is equal to $\mathcal{L}(2\Delta\, w - \Delta)$.] We estimated the following two models:

(1) $p = q = 1$ (Uniform distribution),

(2) $p = q = 2$.

For $\Delta = 0$, we interpret (6.5) as $m_{i,j} = \theta_j$ (almost sure). Both in (1) and (2) we fix $\theta_1 \equiv 3.5$ and $\theta_4 \equiv 6.5$ by means of normalization. The estimation results are summarized in Table 6.2.

There is hardly any difference in the parameter estimates corresponding to the explanatory variables as compared to the deterministic case [Table 6.1, (1)]. However, the estimates for σ_1 and σ_2 are lower in the case of the random thresholds. Part of the variation is now shifted to the thresholds. Estimates for ρ also differ. Those estimates, together with σ_1 and σ_2, imply that the covariance is lower in the case of the random thresholds. This is due to the assumption that the thresholds do not vary across the two valuated products. Again, part of the covariance structure is shifted to the thresholds.

As mentioned before, in the case $\Delta = 0$, the model with random thresholds reduces to the model with constant thresholds. An approximate (95%) confidence interval for Δ in the case of the Beta(2,2) distribution [Table 6.2, (2)] does not contain 0, which supports random thresholds. Further, note that in both cases in Table 6.2, the value of the LLF respectively is increased from −1680.3 to −1674.6 and −1674.1. An interesting hypothesis to test is $\Delta = 0$ versus $\Delta > 0$ (deterministic thresholds versus random thresholds). But since $\Delta = 0$ is a parameter value on the boundary of the parameter space, we cannot make use of the usual ML-based tests. Therefore we consider a subproblem.

Table 6.2 random thresholds
(standard errors in parentheses)

	(1) $\frac{m_j-(\theta_j-\Delta)}{2\Delta} \sim \mathrm{U}(0,1)$		**(2)** $\frac{m_j-(\theta_j-\Delta)}{2\Delta} \sim \mathrm{Beta}(2,2)$	
parameter	estimate		estimate	
constant	1.97	(0.21)	2.00	(0.21)
dumT1	-0.0704	(0.039)	-0.0692	(0.040)
dumT2	-0.0620	(0.038)	-0.0599	(0.039)
age/10	-0.289	(0.067)	-0.272	(0.065)
$(\text{age}/10)^2$	0.0350	(0.010)	0.0328	(0.010)
sex	0.0746	(0.051)	0.0807	(0.049)
fam size	0.0426	(0.029)	0.0377	(0.028)
ch < 15	0.0210	(0.026)	0.0186	(0.025)
chocolate	0.540	(0.030)	0.530	(0.031)
caramel	0.317	(0.026)	0.313	(0.027)
biscuit	0.149	(0.027)	0.144	(0.027)
θ_1	3.5		3.5	
θ_2	4.33	(0.045)	4.33	(0.048)
θ_3	5.19	(0.038)	5.18	(0.038)
θ_4	6.5		6.5	
σ_1	0.664	(0.029)	0.669	(0.026)
σ_2	0.759	(0.029)	0.760	(0.027)
ρ	0.667	(0.025)	0.599	(0.027)
Δ	0.413	*	0.341	(0.029)
LLF	-1674.6		-1674.1	

* Since $\Delta = \frac{1}{2}\min_j(\theta_j - \theta_{j-1})$ – and so it lies on the boundary of the parameter space – it is difficult to give a reliable standard error.

In the deterministic case [Table 6.1, (1)], $\Delta = 0$. This will be model A. Model B will be the random case [Table 6.2, (1)] with $\Delta = \frac{1}{2}\min_j(\theta_j - \theta_{j-1})$. This implies two *strictly non-nested* models. Then we can use a model selection test for strictly non-nested models described by Vuong (1989).

Vuong described a test based on the total loglikelihood and the separate loglikelihood contributions of each observation. Given a pair of competing models, the model that is closest to the "true" model is selected. Under the null hypothesis, the test statistic has a standard normal limit distribution (see, for details, Vuong, 1989). In our context, the two competing models are model A and model B. The realization of the test statistic (Vuong, equation 5.6) is -1.83. This outcome gives us an indication that our extended ordered response model outperforms the standard version.

The next section displays the results when estimating a bivariate ordered probit model for the different product characteristics (chocolate, caramel and biscuit taste). The improvement obtained by random thresholds is even more obvious.

6.4.3 Product characteristics

As mentioned in Section 6.4.1, individuals evaluated the three product characteristics (chocolate, caramel and biscuit taste) on a five-point scale ranging from very bad (1) to very good (5). In the previous section we used the chocolate, caramel and biscuit taste as explanatory variables. This section analyzes each product characteristic separately and gives us another opportunity to compare deterministic and random thresholds. [For the random thresholds we will choose $w \sim \mathrm{Beta}(2, 2)$ [see (6.5)]. In each estimated model, Δ lies on the boundary of the parameter space, and so no standard error is calculated (see note Table 6.2)].

We present the estimation results in Appendix 6.C. The major aim for the estimations of the bivariate ordered probit models for the separate product characteristics is the additional opportunity to compare deterministic thresholds with random thresholds. Tables 6.C.1, 6.C.2 and 6.C.3 show that the LLF is reduced by a rather large amount. The standard errors of all parameter estimates are (slightly) reduced (except for ρ). We can use Vuong's test in the same way as we did in the previous section. The results for all three cases are presented in Table 6.3.

Compare the test statistics in Table 6.3 with the critical value (-1.96), and it can be concluded that the random thresholds are a significant improvement. In these cases the improvement is even more obvious than in the previous section. We also estimated a model with uniform distributed random thresholds. This yielded the same significant improvement. Finally, we tested the uniform distributed random thresholds versus Beta(2,2) distributed random thresholds, again by using Vuong's test. In neither of the three models was the null hypothesis (both models fit the data equally well) rejected, except in the case of biscuit taste. In this case, the Beta(2,2) distribution for the thresholds was significantly better than the uniform distribution.

Table 6.3: comparison of deterministic and random boundaries (see also Appendix 6.C)

model for:	LLF in case of deterministic thresholds	LLF in case of random thresholds	Vuong's test statistic
chocolate taste	-1472.4	-1446.8	-3.22
caramel taste	-1603.6	-1585.4	-3.21
biscuit taste	-1523.2	-1485.6	-4.72

6.5 Concluding remarks

This chapter discussed some extensions of the basic ordered response model. These extensions allow for a possible individual effect in the scale on which the individuals classify their opinion. The emphasis was on the interpretation of the model. The random thresholds entail the elimination of the assumption of constant thresholds. Besides the better interpretation of the model, the relaxation of the constant thresholds may lead to a better fit.

Although Terza (1985) found in an application (concerning bond rating determinants) significance of all the parameters appearing in the linear relationship for the thresholds, we found no significance in our application. On the contrary, we presented some evidence by the use of random thresholds that there is an individual specific effect in the scale on which the individuals classify their opinion.

In the application, we used only two examples of possible distributions for the random thresholds. It should be further investigated whether the estimates of the parameters of interest are sensitive to the chosen distribution.

6.A Appendix: likelihood contributions

This appendix presents the likelihood contributions in the case of the extended (univariate) model. For the ease of notation, we drop the index i corresponding to the i-th individual.

Define

$$
\begin{aligned}
A_j &\equiv \{m_j < y^*\} && j = 1, \ldots, p-1 \\
B_k &\equiv \{\text{"}\underline{\text{exactly}}\ k \text{ of the } A_j\text{'s do occur"}\} && k = 1, \ldots, p-2 \\
S_j &\equiv \sum_{1 \le i_1 < \ldots < i_j \le p-1} \cdots \sum P(A_{i_1}, \ldots, A_{i_j}) && j = 1, \ldots, p-1
\end{aligned}
$$

then

$$
P(B_k) = \sum_{r=0}^{p-1-k} (-1)^r \binom{k+r}{r} S_{k+r}.
$$

Let f denote the density function of y^*. The likelihood contributions can then be written as

$$
\begin{aligned}
P(y=1) &= \int_{-\infty}^{\infty} [\, \prod_{j=1}^{p-1} (1 - P(A_j))\,] f(y^*) dy^*, \\
P(y=k) &= \int_{-\infty}^{\infty} P(B_{k-1}) f(y^*) dy^* \quad (k = 2, \ldots, p-1), \\
P(y=p) &= \int_{-\infty}^{\infty} [\, \prod_{j=1}^{p-1} P(A_j)\,] f(y^*) dy^*.
\end{aligned}
$$

6.B Appendix: descriptive statistics

Table 6.B.1 Number of observations in each cell

y_1 \ y_2	1	2	3	4	5	6	7
1	2	0	0	0	1	0	0
2	1	0	0	0	0	0	0
3	0	1	2	9	2	1	0
4	0	1	6	30	24	13	2
5	0	0	6	31	87	92	9
6	1	1	6	23	104	221	77
7	1	0	0	2	8	30	59

Table 6.B.2 Summary statistics

variable		mean	std.	min.	max.
sex		1.52	0.50	1	2
age	males	28.71	16.01	9	87
	females	29.90	14.85	9	82
	total	29.34	15.42	9	82
fam size		4.22	1.27	1	9
ch $<$ 15		1.44	1.31	0	7
chocolate taste	T1	3.72	0.75	1	5
	T2	3.69	0.75	1	5
	T3	3.74	0.75	1	5
caramel taste	T1	3.58	0.75	1	5
	T2	3.56	0.76	1	5
	T3	3.55	0.80	1	5
biscuit taste	T1	3.51	0.81	1	5
	T2	3.54	0.81	1	5
	T3	3.60	0.78	1	5

6.C Appendix: product characteristics

Chocolate taste

To determine the overall opinion about the chocolate taste we use the following variables: strength of chocolate taste, creaminess of chocolate and quantity of chocolate. Each of these variables can take three values: too little/weak (1), exactly right (2), too much/strong (3). This results in the following set of dummy variables:

strength1 : 1 if strength of chocolate taste is too weak; 0 otherwise,
strength2 : 1 if strength of chocolate taste is exactly right; 0 otherwise,
strength3 : 1 if strength of chocolate taste is too strong; 0 otherwise,
cream1 : 1 if creaminess of chocolate is too little; 0 otherwise,
cream2 : 1 if creaminess of chocolate is exactly right; 0 otherwise,
cream3 : 1 if creaminess of chocolate is too much; 0 otherwise,
quantity1 : 1 if quantity of chocolate is too little; 0 otherwise,
quantity2 : 1 if quantity of chocolate is exactly right; 0 otherwise,
quantity3 : 1 if quantity of chocolate is too much; 0 otherwise.

For identification purposes, we fix the coefficients corresponding to the variables strength2, cream2 and quantity2 at 0. The results are displayed in Table 6.C.1.

Table 6.C.1: chocolate taste (standard errors in parentheses)

	deterministic thresholds		**random thresholds**	
parameter	estimate		estimate	
constant	3.94	(0.036)	3.93	(0.033)
strength1	-0.757	(0.041)	-0.680	(0.037)
strength3	-0.503	(0.052)	-0.453	(0.048)
cream1	-0.487	(0.042)	-0.429	(0.039)
cream3	-0.324	(0.063)	-0.297	(0.054)
quantity1	-0.0562	(0.043)	-0.0614	(0.038)
quantity3	-0.189	(0.066)	-0.170	(0.062)
θ_1	1.5		1.5	
θ_2	2.07	(0.050)	2.27	(0.039)
θ_3	3.17	(0.037)	3.25	(0.029)
θ_4	4.5		4.5	
σ_1	0.698	(0.022)	0.603	(0.018)
σ_2	0.703	(0.024)	0.582	(0.024)
ρ	0.647	(0.020)	0.565	(0.025)
Δ	0		0.387	
LLF	-1472.4		-1446.8	

The most important component contributing to the chocolate taste is the strength. Individuals evaluated the chocolate taste in the case of a "too weak" strength worse than they did in the case of a "too strong" strength of the chocolate taste. The same holds for the creaminess of the chocolate. With regard to the quantity of the chocolate, only "too much" chocolate significantly lowers the valuation.

Caramel taste

To determine the overall opinion about the caramel taste we use the following variables: strength of caramel taste, chewiness of caramel and quantity of caramel. The analysis is analogous to the previous case (instead of cream1, cream2 and cream3, we now have chew1, chew2 and chew3). The results are displayed in Table 6.C.2.

Table 6.C.2: caramel taste (standard errors in parentheses)

	deterministic thresholds		**random thresholds**	
parameter	estimate		estimate	
constant	3.85	(0.038)	3.85	(0.034)
strength1	-0.907	(0.047)	-0.841	(0.046)
strength3	-0.440	(0.044)	-0.410	(0.043)
chew1	-0.300	(0.050)	-0.288	(0.048)
chew3	-0.312	(0.044)	-0.305	(0.042)
quantity1	-0.196	(0.043)	-0.191	(0.042)
quantity3	-0.194	(0.048)	-0.175	(0.046)
θ_1	1.5		1.5	
θ_2	2.11	(0.049)	2.22	(0.039)
θ_3	3.28	(0.036)	3.31	(0.031)
θ_4	4.5		4.5	
σ_1	0.700	(0.025)	0.633	(0.023)
σ_2	0.723	(0.024)	0.650	(0.024)
ρ	0.604	(0.023)	0.548	(0.028)
Δ	0		0.362	
LLF	-1603.6		-1585.4	

Table 6.C.2 shows that an evaluation "too weak" with regard to chewiness has the same impact as that of "too strong" with regard to chewiness of the caramel. The same is true for the quantity of the caramel. Regarding the strength of the caramel taste, a significant difference appears between evaluations "too weak" and "too strong."

Biscuit taste

To determine the overall opinion about the biscuit taste, we use the following variables: strength of biscuit taste, crispiness of biscuit and quantity of biscuit. Instead of chew1, chew2 and chew3, we now have crisp1, crisp2 and crisp3. The results are displayed in Table 6.C.3.

Table 6.C.3: biscuit taste (standard errors in parentheses)

	deterministic thresholds		**random thresholds**	
parameter	estimate		estimate	
constant	3.74	(0.036)	3.75	(0.032)
strength1	-0.751	(0.043)	-0.690	(0.041)
strength3	-0.506	(0.046)	-0.466	(0.044)
crisp1	-0.422	(0.042)	-0.395	(0.040)
crisp3	-0.343	(0.053)	-0.321	(0.050)
quantity1	-0.181	(0.048)	-0.173	(0.045)
quantity3	-0.245	(0.043)	-0.243	(0.040)
θ_1	1.5		1.5	
θ_2	2.17	(0.041)	2.32	(0.031)
θ_3	3.16	(0.034)	3.22	(0.028)
θ_4	4.5		4.5	
σ_1	0.677	(0.022)	0.585	(0.021)
σ_2	0.703	(0.022)	0.603	(0.020)
ρ	0.689	(0.019)	0.617	(0.025)
Δ	0		0.410	
LLF	-1523.2		-1485.6	

Only the strength of the biscuit taste has different parameter values with respect to evaluations "too weak" and "too strong." A "too weak" evaluation of the biscuit taste is valuated worse than "too strong." For the crispiness and quantity, no difference was found if it is "too weak/little" or "too strong/much." Both extremes lower the valuation for the biscuit taste to the same extent.

Chapter 7

Summary and Conclusions

This thesis concentrates on the use of subjective data in micro-econometric analyses – in particular subjective information on household income growth and uncertainty. The emphasis is on the feasibility and usefulness of the subjective data. For this purpose, we use two Dutch panels. The first one is the Dutch Socio-Economic Panel (SEP), which is administered by Statistics Netherlands, and the second one is the VSB panel, which has been devised by researchers at CentER for Economic Research at Tilburg University.

Income expectations play a central role in household decision making. In the life cycle model, for example, consumption and savings decisions reflect expectations of future income. In empirical applications that have no direct information on expectations, it is usually assumed that expectations are rational, and reflected by observed realizations.

Chapter 2 analyzes direct measurement of expected income changes. Data come from the first wave of the SEP. Heads of households are asked to answer the question

> *What will happen to your household's income in the next twelve months?*

Possible answers to this question are the following: strong decrease, decrease, no change, increase, and strong increase. For the wave under consideration, slightly more than 50% do not expect their current income to change, which means that realized household income is a dominant predictor of expected household income.

Since the answer to the above mentioned question is a discrete variable with a natural ordering, we estimate an ordered probit model explaining expected income changes from income changes in the past, the level of actual income, and other background variables, such as age, family composition, and labor market status. We find that those who experienced a strong income decrease in the past twelve months are less optimistic about future income growth than the reference group of those who experienced no change. Similarly, those whose incomes increased in the past twelve months are more optimistic than the reference group. Household income growth expectations tend to be more pessimistic the older the head of household is. The relatively optimistic view of younger people could be explained by the fact that earnings increases are usually much larger in the beginning of a working career. With respect to the level of actual income, we find a positive correlation: the higher the income, the more often the head of household expects an increase in family income growth.

Heads of households are also asked to answer the question

> *Did your household's income increase, decrease, or remain unchanged during the past twelve months?*

Although the questions are not very well specified, it seems reasonable to assume that the head of household has the same concept in mind while answering both questions on realized and expected income change. (Both questions appear in the questionnaire close to each other.) This gives us the opportunity to compare the expectation in one year to the realization the next year. We find that particularly those who experienced an income decrease in 1984, tend to underestimate their income growth in 1985. Since it is hard to explain this finding from a macro-economic shock, this might be evidence against the rational expectations hypothesis.

Chapter 3 checks the robustness of the results we find in Chapter 2. In Chapter 3 we again analyze subjective expectations about future income changes, but then using panel data instead of one cross section. The models used are extensions of existing binary choice panel data models to the case of ordered response. We consider both random and fixed individual effects. The extension in case of random effects is straightforward and the model is estimated by maximum likelihood. In the fixed effects, however, the number of parameters increases with the number of respondents and maximum likelihood estimates will be inconsistent if the number of respondents goes to infinity but the number of time periods is finite. For the binary choice panel data model, Chamberlain (1980) suggested an approach based upon a conditional likelihood to estimate the parameters of interest. The key idea is to condition on sufficient statistics for the nuisance parameters. This idea works if the disturbance terms are i.i.d. and follow a logistic distribution. A direct extension of this approach to an ordered response panel data model is not straightforward and even seems impossible. We can, however, combine adjacent categories and then use the conditional logit method of Chamberlain. The final fixed effect estimator is then obtained by combining all possible conditional fixed effects logit estimates using a minimum distance step.

Data come from the October waves of 1984 through 1989 of the SEP. The 1984 estimates in the model for the income growth expectations are similar to those in Chapter 2. Many of these appear to remain stable over time. For all panel waves we find that income growth expectations are strongly affected by previous income changes. The impact of labor market status variables is less stable over time, and this can partly be explained by institutional changes in the time period considered. For the unemployed and disabled family heads, for example, differences in income growth expectations with workers decline and have basically disappeared in the last wave. For the disabled, this may well reflect anticipation of the institutional changes in disability benefit access and levels that started in 1985 and were completed in 1987. For the unemployed, it probably reflects larger expected changes of finding a job due to the upswing of the business cycle.

The results in the random and fixed effects specification are basically the same. Only for the level of actual income do we find a different result. An explanation is that the fixed individual effect is positively correlated with income. The results of the random effects model tell us that those with higher permanent incomes generally have higher expected income growth than others. Conditional on the fixed effect and permanent income, however, we find that those with low or negative transitory often expect an income rise, while those with a high transitory income expect their income to fall.

Comparing expected and realized income changes for the same time period, we find for all waves but one that on average, future income growth was significantly underestimated. This holds, in particular, for families whose incomes have fallen in the past twelve months. It seems hard to imagine that this result is caused by an unanticipated macro-economic shock. First, we cannot think of shocks which would affect only those with a specific income change and not a specific income level. Second, the effect is remarkably persistent over time. Another explanation seems to be that people's expectations are not rational, and that negative transitory incomes are too often considered to be permanent.

A plausible alternative explanation for the finding that there exists an overall tendency of underestimation is given in Manski (1990). Due to the fact that we are comparing an *ex ante* location measure with an *ex post* realization, and due to the categorical nature of the data, the number of people underestimating and overestimating future income growth are not necessarily the same. We do not think that this argument can explain why particularly those whose incomes fell in the past underestimate, but it might explain the overall tendency of underestimation. Therefore, this "statistical artifact" is analyzed in more detail in the next chapter, Chapter 4.

Manski studied the comparison of expected and realized outcomes for the case of a binary variable. Since the qualitative data we use can take more than two outcomes, we first extend Manski's analysis to the general case of multiple-ordered-category expectations. We consider three models generating best predictions of the prospective outcomes. Each model is based on a different expected loss function that respondents minimize. For each case we derive bounds on features of the distribution of realizations. In contrast to Manski's analysis of the binary case, different symmetric loss functions may yield different multiple-ordered-category survey responses and therefore imply different bounds.

The three possible location measures of the subjective distribution of the variable of interest are the modal category, the median or α-quantile, and the mean assumption. The former two can be applied if comparable categorical data on predictions or expectations and outcomes are available, while the latter can only be applied if the actual outcome is measured as a continuous variable. Since we have both qualitative and quantitative data, we can carry out tests on all three underlying assumptions.

We repeat the comparison of expected and realized income growth as carried out in Chapters 2 and 3. On the basis of the categorical realizations data, we find the same results for the modal and median category assumption: the hypothesis that respondents have rational expectations and report best predictions of future outcomes is rejected for the group of households expecting a moderate income decrease. For too many of these, realized income did not change and they appeared to be too pessimistic, on average. Based on quantitative data on realized income, the mean assumption leads to the same conclusion, although the results are not always as significant as under the modal and mean assumption.

One interpretation of the findings is that people have asymmetric loss functions. We investigated this with more general α-quantile assumptions. The categorical data do not support a single value of α, but using an alternative continuous measure of household income change, we conclude that values of α lower than 0.5 could be plausible. This would mean that respondents tend to place more weight in their loss function on negative forecast errors,[1] which leads to underestimation (on average). Another interpretation of our findings is that, even if we take into account that there is a limited amount of information in qualitative data, substantial groups of households do not have rational expectations.

Up to Chapter 5, the thesis concentrates on the use of qualitative data. The panel nature of the SEP is fully exploited and subjective categorical data on expected and realized income changes are analyzed. Chapter 5 discusses a more recently used method of eliciting information on the subjective distribution of future income. This chapter uses data from the Dutch VSB panel, which started in 1993. The survey method is completely computerized. In the 1995 wave of this panel, heads of households are asked to indicate a range over which their household income could vary over the next twelve months. After that, the respondents are asked to evaluate the probability 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 indicated range. The answer to these questions correspond to values of the subjective distribution function of next year's household income and are used to construct a subjective measure of income uncertainty.

In choosing a measure of income uncertainty, we use the interquartile range of the subjective distribution of next year's income. To calculate this interquartile range, we assume both a parameter free distribution and distributions known up to a parameter vector. This parameter vector is then estimated using our data. For example, we choose a lognormal distribution, with the median and interquartile range as unknown parameters.

We compare our measure of income uncertainty with two corresponding studies. Dominitz and Manski (1997) collected data on the one-year-ahead income expectations of members of American households in their Survey of Economic Expectations. The other study is conducted in Italy, where the Bank of Italy's biennial survey of the Italian population asked questions eliciting probabilistic income expectations. We find that perceived income uncertainty in the U.S. is larger than in each of the two European countries.

Chapter 5 also examines how our measure of income uncertainty varies with household characteristics. Controlling for information on expected changes, we find strong

[1] A negative forecast error is here defined as realization minus expectation being negative.

relationships between labor market characteristics and the subjective income uncertainty as reported by the head of household. We find a positive effect of a working partner on income uncertainty. This effect increases when a partner is unemployed and searching for a job. A female head of household perceives less income uncertainty than does a male.

The next chapter, Chapter 6, deviates from the previous chapters in that it focuses neither on income expectations nor income uncertainty. This chapter focuses on ordered response models, which are used to model ordered categorical data. In Chapters 2 and 3 we make use of these kind of data.

In an ordered response model, the observed categorical variable is based upon classifying an underlying latent variable into one out of a finite number of intervals. In the model used in Chapter 2, and in the random effects specification in Chapter 3, the threshold parameters of these intervals are assumed to be unknown deterministic parameters. In the fixed effects specification in Chapter 3, however, the threshold parameters are allowed to be individual specific, since the sufficient statistic for the individual effect is also a sufficient statistic for the thresholds. Such individual specific threshold parameters seem to be more realistic than constant thresholds. Chapter 6 discusses extensions of the basic ordered response model that entail eliminating the assumption of constant thresholds.

The first extension, which is proposed by Terza (1985), assumes the thresholds to be a linear function of known explanatory variables. The second extension we propose does not specify a functional relationship between thresholds and known explanatory variables, but assumes random thresholds. We discuss both the univariate and the multivariate cases. An application, which is meant only to be illustrative, indicates that the random boundaries significantly improve the basic ordered response model.

Returning to the aim of our study, findings in this thesis show that subjective data are reliable. The relation of the subjective qualitative income expectations to various background variables are rather robust over time and of the expected sign. A first attempt is made to use detailed information on individuals' subjective income distributions that can be used to construct a measure of income uncertainty.

Another finding in this thesis is that the subjective data conflict with the usual assumptions on rational expectations and (absence of) macro-economic shocks. In that respect, subjective information might be useful. A topic for future research would be to explicitly incorporate subjective data in models explaining household behavior. In recent studies some first attempts have been made to use subjective information. Guiso et al. (1992) and Alessie et al. (1995), for example, use the answers to subjective questions as explanatory variables in a regression equation to explain consumption and wealth accumulation. One step further would be to build a more structural model in which subjective information is used. In a standard life cycle model, for example, one usually assumes that consumers plan over their complete lifetime and maximize expected utility where the expectations are formed rationally. This thesis suggests that rational expectations might be too strong an assumption. Therefore, a relevant topic of future research would be to investigate how the subjective income expectations studied in this thesis can be incorporated in these type of models. Since the assumption that consumers take their whole lifetime into account seems to be a strong one from an economic point of view, and rather complicated from an econometric point of view, a two period model in which consumers decide on present consumption and savings would be a good starting point.

Another topic for future research is to provide a framework to fully exploit the richness of the (qualitative) expectations and realizations data. That is, use an explicit model of how respondents answer the expectations questions (see Chapter 4), and then simultaneously estimate this model and the model explaining the deviations of expectations from subsequent realizations. In addition, we can build a structural model that also uses the quantitative information on actual income.

A natural extension of the analysis in Chapter 5 is to consider more waves. Then it would be possible to examine how the income uncertainty varies over time and whether the subjective measure of uncertainty really reflects income uncertainty or whether it also picks up some life-time uncertainty. The questions used in this chapter are quite promising, providing detailed information on the subjective distribution of a future variable rather than only indicating to which category this variable belongs. An issue that is not covered in this thesis is the evaluation of these type of questions by the respondents themselves. Do they prefer this way of responding, and more importantly, are they able to think in terms of cumulative probabilities? Although this might be more a topic for (economic) psychologists, it is still interesting and necessary to know how information from respondents can be optimally transferred to the researcher.

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Samenvatting

Verwachtingen omtrent de toekomst staan vaak centraal in economische gedragsmodellen. Als voorbeeld kan het levenscyclusmodel worden beschouwd waarin individuen of huishoudens hun beslissingen met betrekking tot consumptie niet alleen baseren op het huidige inkomensniveau, maar ook rekening houden met het toekomstige inkomen. Het is in het algemeen niet waargenomen hoe mensen hun verwachtingen bepalen en vaak is er ook geen informatie beschikbaar over hoe die verwachtingen eruit zien. Meestal wordt dit probleem omzeild door veronderstellingen ten aanzien van het verwachtingspatroon te maken. Vervolgens wordt dit verwachtingspatroon als onderdeel van het economische gedragsmodel geformuleerd. Een populaire aanname is dat economische agenten hun beslissingen baseren op rationele verwachtingen. In de meest gangbare formulering houdt de rationele verwachtingen hypothese in dat agenten alle volgens het model beschikbare informatie gebruiken om hun verwachtingen in overeenstemming met de werkelijkheid (of het, als waar beschouwde, model) te vormen.

In vele onderzoeken is de rationele verwachtingen hypothese reeds (empirisch) getoetst. Economen geven in het algemeen de voorkeur aan een indirecte methode van toetsing, waarbij het verwachtingspatroon wordt geschat en getoetst op grond van geobserveerde feitelijke uitkomsten. Een belangrijk nadeel van deze methode is dat moet worden aangenomen dat het vooraf gespecificeerde model voor verwachtingen waar is, al dan niet in samenhang met het economische gedragsmodel waarin men uiteindelijk is geïnteresseerd.

De directe methode vermijdt de noodzaak van het formuleren van een model voor verwachtingen. In deze methode wordt economische agenten expliciet naar hun toekomstverwachtingen gevraagd. Deze methode is niet zo populair bij economen. Hun skepticisme is hoofdzakelijk gebaseerd op het feit dat individuen geen prikkel hebben om de vragen zorgvuldig te beantwoorden. Echter, indien deze kritiek terecht is, dan betreft die ook ingevulde enquêtes die betrekking hebben op gerealiseerd inkomen, bezittingen, werkstatus en andere gegevens, op grond waarvan tal van economische analyses van gedrag zijn gebaseerd.

Dit proefschrift gaat over subjectieve data omtrent toekomstverwachtingen, in het bijzonder over antwoorden op vragen naar verwachtingen omtrent toekomstige inkomensgroei. Doel van het proefschrift is niet om met behulp van subjectieve data economische gedragsmodellen te schatten, maar de nadruk ligt meer op het onderzoeken van de betrouwbaarheid en bruikbaarheid van subjectieve informatie. Hiervoor maken we gebruik van twee Nederlandse panels: het Sociaal-Economisch Panel (SEP) van het Centraal Bureau voor de Statistiek en het VSB panel, dat is ontworpen door onderzoekers van CentER.

Hoofdstuk 1 is inleidend en bevat een overzicht van het proefschrift.

Hoofdstuk 2 analyseert subjectieve informatie omtrent de verwachte inkomensveranderingen op huishoudniveau. De gebruikte data komen uit de eerste golf van het SEP (1984). Het hoofd van elk huishouden is gevraagd hoe het huishoudinkomen de komende twaalf maanden naar verwachting zal veranderen. De mogelijke antwoorden zijn: sterk dalen, dalen, geen verandering, stijgen, sterk stijgen. Om te bepalen in hoeverre het antwoord op de vraag varieert met verschillende huishoudkarakteristieken, wordt een *ordered response model* geschat. Met name de huishoudens waarvan het inkomen in de afgelopen twaalf maanden is gedaald, zijn minder optimistisch omtrent toekomstig inkomen dan de referentiegroep van gezinnen waarvan het inkomen in de afgelopen twaalf maanden niet is veranderd. Analoog blijken huishoudens waarvan het inkomen in de afgelopen twaalf maanden is gestegen, optimistischer dan de referentiegroep. Het optimisme omtrent toekomstige inkomensgroei daalt naarmate het hoofd van het huishouden ouder is. Het hoofd van het huishouden verwacht vaker een stijging in het toekomstige inkomen naarmate het huidige huishoudinkomen hoger is.

Naast de vraag in hoeverre het hoofd van het huishouden een verandering in toekomstig inkomen verwacht, wordt tevens de vraag gesteld in hoeverre het inkomen in de afgelopen twaalf maanden is veranderd. Hierbij worden dezelfde antwoordcategorieën gehanteerd. Het lijkt aannemelijk dat bij het beantwoorden van beide vragen hetzelfde concept wordt gebruikt, waardoor verwachting en realisatie vergelijkbaar zijn. Gebruikmakend van de verwachte inkomensgroei voor de komende 12 maanden in de golf van oktober 1984 en de gerealiseerde inkomensgroei in de afgelopen 12 maanden in de golf van oktober 1985, vinden we dat met name huishoudens waarvan het inkomen in de twaalf maanden voor oktober is gedaald de inkomensgroei onderschatten in de periode okt. 1984 - okt. 1985.

De belangrijkste kritiek op de analyse in Hoofdstuk 2 is dat de bevindingen gevoelig kunnen zijn voor het specifieke jaar dat wordt beschouwd. Zo kunnen macro-economische schokken de resultaten beïnvloeden. Een uitgebreidere studie is beschreven in Hoofdstuk 3. In dit hoofdstuk wordt een panel data model geschat op basis van de SEP-golven van 1984 tot en met 1989. Op deze manier wordt nagegaan of de resultaten van Hoofdstuk 2 robuust zijn.

Hoofdstuk 3 schat modellen die een uitbreiding vormen van reeds bestaande binaire keuzemodellen. Vanwege het panel karakter van de data is het mogelijk om een individu specifieke parameter in het model op te nemen. De resultaten van Hoofdstuk 2 blijken stabiel over de tijd. Voor iedere golf vinden we dat verwachtingen omtrent inkomensgroei sterk worden beïnvloed door de inkomensverandering in het verleden. Voor wat de arbeidsmarktstatus van het hoofd van het huishouden betreft, zijn de resultaten minder stabiel over de tijd. Dit kan gedeeltelijk worden verklaard door de institutionele veranderingen in de tijdsperiode die wordt beschouwd, zoals veranderingen in de regels voor arbeidsongeschiktheidsuitkeringen.

Indien we verwachte en gerealiseerde inkomensgroei voor dezelfde perioden met elkaar vergelijken, vinden we dat voor iedere golf de toekomstige inkomensgroei wordt onderschat. Dit resultaat is met uitzondering van één golf statistisch significant. Bovendien geldt de onderschatting voor met name de huishoudens die de afgelopen twaalf maanden een daling in het inkomen hebben ervaren. Het lijkt moeilijk voor te stellen dat dit resultaat veroorzaakt wordt door (niet geanticipeerde) macro-economische schokken. Het resultaat is opmerkelijk stabiel over de tijd. Dit suggereert dat we kunnen concluderen dat verwachtingen omtrent toekomstige inkomensgroei niet rationeel zijn, en dat negatieve schokken in het verleden te vaak als permanent worden beschouwd.

Een kritiek op het gebruik en de vergelijking van kwalitatieve data, zoals in de Hoofdstukken 2 en 3, is geformaliseerd door Manski (1990). In zijn artikel wordt aangetoond dat kwalitatieve gegevens over verwachtingen en realisaties niet zonder meer vergeleken kunnen worden. De reden hiervoor is dat de opgegeven verwachting een kengetal van de individuele subjectieve verdeling is, terwijl de realisatie een trekking uit de verdeling weergeeft. Hoofdstuk 4 generaliseert Manski's kritiek naar de situatie met meer categorieën. We beschouwen drie modellen die verwachtingen omtrent de toekomst genereren. Aan ieder model ligt een andere verwachte verliesfunctie die agenten minimaliseren, ten grondslag.

We herhalen de vergelijking van verwachte en gerealiseerde inkomensgroei en vinden hetzelfde resultaat als in Hoofdstuk 3: de toekomstige inkomensgroei wordt onderschat. Een mogelijke interpretatie van dit resultaat is dat agenten een asymmetrische verliesfunctie hanteren. Dit zou betekenen dat respondenten de neiging hebben om meer gewicht op het overschatten van toekomstige inkomensgroei in hun verliesfunctie te plaatsen, hetgeen (gemiddeld) tot onderschatting leidt. Hoewel de kwalitatieve data deze interpretatie niet eenduidig ondersteunen, is op grond van een alternatieve (op kwantitatieve data gebaseerde) maat van inkomensverandering deze interpretatie plausibel.

In Hoofdstuk 5 wordt een recente methode toegepast om informatie in kaart te brengen omtrent de subjectieve verdeling van het toekomstige huishoudinkomen. In dit hoofdstuk maken we gebruik van data uit het VSB panel. In de golf van 1995 wordt hoofden van huishoudens gevraagd om het bereik van hun subjectieve verdeling van het toekomstige huishoudinkomen aan te geven. Daarna wordt hun gevraagd de kans te geven dat het toekomstige huishoudinkomen onder een bepaald niveau zal liggen. De antwoorden op deze vragen corresponderen met waarden van de subjectieve inkomensverdeling en worden gebruikt om een maat voor inkomensonzekerheid af te leiden.

Hoofdstuk 5 analyseert hoe de afgeleide maat voor inkomensonzekerheid varieert met diverse huishoudkarakteristieken. Daarnaast wordt de gevonden mate van inkomensonzekerheid vergeleken met resultaten uit de Verenigde Staten en Italië. We vinden dat de inkomensonzekerheid in de Verenigde Staten groter is dan in Italië en Nederland.

Hoofdstuk 6 verschilt van de voorgaande hoofdstukken aangezien het zich niet concentreert op inkomensverwachtingen of inkomensonzekerheid. In dit hoofdstuk wordt een methodologisch aspect van *ordered response modellen* onder de loep genomen. In een *ordered response model*, zoals in Hoofdstuk 2, is de geobserveerde discrete variabele gebaseerd op het classificeren van een onderliggende latente variabele in verschillende intervallen. De grenzen van deze intervallen zijn deterministisch en worden met behulp van de data geschat. Dit betekent dat volgens dit model iedere respondent dezelfde intervallen ter bepaling van het (geobserveerde) antwoord gebruikt. Hoofdstuk 6 beschouwt enkele uitbreidingen naar individu specifieke intervalgrenzen.

De eerste uitbreiding is gebaseerd op Terza (1985) en veronderstelt dat de intervalgrenzen een lineaire functie zijn van huishoudkarakteristieken. Een tweede uitbreiding, waarbij geen functionele relatie wordt opgelegd, verondersteld stochastische grenzen. Dit betekent dat wordt toegelaten dat mensen met dezelfde geobserveerde karakteristieken toch verschillende intervalgrenzen hanteren. In een applicatie, die dient ter illustratie, vinden we aanwijzingen dat stochastische grenzen een significante verbetering van het oorspronkelijke *ordered response model* vormen.

Hoofstuk 7 geeft een korte samenvatting en conclusies. Het proefschrift geeft aan dat subjectieve informatie een zinvolle en bruikbare bijdrage kan leveren aan economische studies. Een natuurlijke volgende stap is het expliciet opnemen van subjectieve data in economische gedragsmodellen.