Precautionary saving, wealth accumulation and pensions

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Precautionary Saving, Wealth Accumulation and Pensions

An Empirical Microeconomic Perspective

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An Empirical Microeconomic Perspective

Proefschrift

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Contents

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Stockholm, November 2012

Chapter 1

Introduction

1.1 Introduction

This thesis bundles four studies on saving for retirement and the role of the pension system. Saving for retirement has been and remains to be an important topic on the policy agenda, and has produced a wide spectrum of research in economics. The four studies aim to contribute to understanding the role of pension systems in the decision how much to save for retirement. A key feature in the first three essays concerns the role of uncertainty in the decision to put money aside, investigated using Dutch microeconomic data, whereas the last study takes a European view on the same topic. Uncertainty in pension income is of particular policy interest in the Netherlands at this moment. The current financial crisis has shown the vulnerability of the Dutch pension funds to bad stock market returns and low interest rates, which puts pension benefits of all participants at risk. This comes on top of the problems due to aging of the population, which increases the social security paycheck. In this introductory chapter, I will first motivate the research and discuss its policy relevance in section 1.2. Second, I present the research questions the thesis aims to answer in section 1.3. Section 1.4 summarizes the main findings of the four studies. The remaining chapters of this thesis present the four studies undertaken. All chapters may be read independently.

1.2 Motivation and contents

The idea of saving for retirement is very old, and broadly ranges from raising children to take care of the elderly parent to investing in a pension fund. In both cases, the individual expects to enter a stage in life without financial resources from labor. Saving for retirement serves to prevent people from starvation after terminating their working career. With the introduction of the Bismarckian welfare state, and in particular the old-age social security system, the government has stepped in to provide their citizens a level of income to finance consumption expenditures. The pension system expanded by the introduction of employer-provided pension plans. In the Netherlands, the social security system (the first pillar of the pension system) covers all citizens of the Netherlands, while around 90% of employees are covered by an occupational pension plan (the second pillar). Together, these two pillars provide generous pension benefits upon retirement from the labor market.

There are multiple economic consequences of the introduction of a pension system, most importantly: 1) reduced fertility, as the elderly parent becomes financially independent of the children (Neher, 1971); 2) changes in labor supply, individuals end their working career (before or) upon reaching the statutory retirement age to claim pension benefits (Stock and Wise, 1990); and 3) reductions in private wealth accumulation. This thesis focuses on the third consequence: how does the provision of public and occupational pensions affect wealth accumulation? In a simple economic setting, the answer to this question is straightforward: each euro received after retirement implies a one euro decrease in savings before retirement. This crowding out effect of private wealth by pension wealth has been predicted in the theoretical literature, starting with Modigliani and Brumberg (1954) and Friedman (1957), and subsequently tested empirically using aggregate data (Feldstein, 1974) and microeconomic data (Dicks-Mireaux and King, 1984; Gale, 1998).[*]

In reality, the economic environment the typical household faces is more complicated than the simple setting described above. The vast majority of the empirical literature uses a version of the lifecycle model based on perfect foresight: individuals can perfectly predict the future. That is, an individual of, say, age 40 knows his future earnings, pension benefits, the rate of inflation, the timing of his death and all other economic variables relevant to making the saving decision. This assumption is convenient in theoretical work and empirical specifications, but is unlikely to be justified in reality. Indeed, as already noted by Keynes (1936), one of the factors influencing the propensity to consume out of income is:

"*Changes in expectations of the relation between the present and the future level of income.* – We must catalogue this factor for the sake of formal completeness. But, whilst it may affect considerably a particular individual's propensity to consume, it is likely to average out for the community as a whole. Moreover, it is a matter about which there is, as a rule, too much uncertainty for it to exert much influence." (Keynes, 1936, Chapter 8)

[*] More extensive literature reviews are presented in the core chapters of the thesis.

From a macroeconomic perspective, Keynes may be right in saying that expectations are not so important for consumption decisions. However, for an individual, expectations of future income may well be very important for explaining behavior. In the first two essays, I allow individuals to be uncertain about the future, and instead model future pension benefits (as a fraction of earnings) as a random variable. To estimate the lifecycle model with uncertainty over pension benefits using microeconomic data, we need to know how uncertain people are over their estimate of future income. Dominitz and Manski (1997) developed a survey methodology to elicit the subjective distribution of a random variable. Their methodological innovation has been used in the Dutch Pension Barometer survey to elicit the subjective distribution of pension benefits for a sample of Dutch employees. In short, instead of asking the respondent to indicate how much pension benefits he expects to receive in the future, the survey asks him to state the probability that his pension benefits are less than 100% of his current income. Asking the same question for different thresholds (for example, less than 70% of current income) then gives the researcher an idea of the shape of the distribution of pension benefits. From this distribution, both the mean and standard deviation, as measures of the expected level of benefits as well as the uncertainty around this estimate, can be computed. Chapter 2 discusses the usefulness of this methodology, and analyzes which factors influence the expected level of and uncertainty over pension benefits. Chapter 3 subsequently uses the expected level pension benefits and the degree of uncertainty to explain household saving, and as such relaxes the assumption of perfect foresight in an empirical lifecycle model.

Chapters 4 and 5 also contribute to the empirical literature on saving for retirement, but, in contrast to chapters 2 and 3, do not focus on relaxing the assumption of income certainty. Chapter 4 recognizes the fact that, although the pension system in the Netherlands is generous, households may still wish to engage in other forms of retirement saving. In particular, households may purchase insurance policies to provide additional sources of income for financing consumption expenditures after retirement. I investigate the demand for both annuities and endowment policies using the DHS panel. Put simply, purchasing an annuity entitles the buyer to a stream of income, starting at a date in the future (for instance, at retirement) and lasting until the buyer dies. An endowment policy instead entitles the buyer to a sum of money, to be received upon a certain date in the future, such as the retirement date. Both products have a tax-preferred nature. Buying an endowment policy has the additional advantage of closing the gap between actions and intentions, by locking money away for a longer period; if one really wishes to save for retirement, but still spends labor earnings on food and drinks, this type of product is particularly suitable for achieving one's goal. An annuity instead has the advantage of paying out as long as one lives. As shown by Yaari (1965), annuities are an attractive product to hedge against becoming very old and running out of wealth. Yet, the empirical evidence suggests low ownership rates for annuities, a phenomenon referred to as the annuity puzzle. The aim of chapter 4 is to investigate which factors influence the demand for annuities and endowment policies, as an attempt to understanding the causes of the annuity puzzle. Moreover, I offer an additional explanation of the annuity puzzle: the low observed rate of ownership of annuities may be an artifact of using survey data. Individuals may report not to own annuities, while in reality they do own an annuity, and vice versa. Our econometric model takes this measurement error problem into account, and estimates the probability of misreporting ownership of both annuities and endowment policies.

Measurement errors play an important role in chapter 5 as well. In this last chapter, I return to the question on the crowding out of private savings by pension savings, taking a European view. The Survey of Health, Aging and Retirement in Europe, SHARE, interviews households in 13 European countries, using the same questionnaire translated in each country's language. The third wave of this survey, called SHARELIFE, is unique in asking these households to give information on their life histories. Since the respondents are at least 50 years old when being interviewed, asking them about their personal history closes a large informational gap. For this study's purposes, the labor market history and past earnings are especially interesting, as they allow the researcher to construct a measure of lifetime earnings. This measure is missing in previous studies estimating the extent of crowding out. Next to using these unique data, the essay shows that measurement error plays an important role in most of the literature. It is well known that measurement error in any of the explanatory factors leads to biases in the estimated model parameters. I show that, in the type of model the literature has built upon, the bias may be large enough to have the researcher draw the wrong, opposite conclusions. The econometric model presented in this chapter, however, always leads the researcher in the right direction. This is important, since the extent of crowding out has important implications for policy makers contemplating a reform of the pension system, as is currently taking place in the Netherlands. Due to population aging and the economic crisis, the pension system has become more fragile, and measures are being discussed to improve the performance of the Dutch pension system. Once we know the extent of crowding out of private wealth by pension wealth, we can more accurately predict the welfare consequences of these reforms. Chapter 5 establishes the methodology for doing just that.

1.3 Research questions

To summarize what this thesis aims to achieve, this section presents the research questions to which the four studies try to provide answers.

Chapter 2 addresses the following questions:

Question 1.1. *Which factors influence the expected level of pension benefits and the uncertainty over pension benefits of Dutch individuals? Are the answers to the probabilistic survey questions useful?*

The research question handled in chapter 3 is

Question 1.2. *How large is the extent of crowding out of private saving by pension saving in the Netherlands, and does uncertainty in pension benefits lead to a precautionary savings?*

In chapter 4, I deal with the following questions:

Question 1.3. *Which factors are important for explaining the ownership rates of annuities and endowment policies for Dutch households? Can measurement errors in observed ownership rates solve the annuity puzzle?*

The last questions, answered in chapter 5, are

Question 1.4. *How large is the extent of crowding out of private wealth by pension wealth in Europe? How useful is retrospective earnings information in answering this question?*

1.4 Main findings

Below, I provide short answers to the research questions posed above.

1.4.1 Chapter 2

On the factors influencing the mean and standard deviation of the distribution of the retirement income replacement rate, chapter 2 shows that, compared to less educated individuals, higher educated individuals expect a statistically significant lower replacement rate and are more uncertain about it. Two (possibly reinforcing) explanations for this finding are as follows. First, since higher educated individuals typically earn higher wages, while the Dutch state pension system is redistributive in nature, they should expect a lower replacement rate than less educated individuals. Furthermore, the career path of higher educated individuals is usually steeper and surrounded by greater uncertainty, making it harder to predict pension benefits, resulting in more subjective uncertainty. Second, these findings may reflect the fact that higher educated individuals are better informed about their future pension entitlements by, for instance, keeping closer track of news and developments regarding their pension income. The recent turmoil on the financial markets following the credit crunch of 2008 affected both state and occupational pensions in the Netherlands, lowering real pension benefits and increasing the eligibility age. Furthermore, recently implemented changes, including the change from final-pay to average-pay occupational pensions and the abolishment of tax-favorable early retirement contributions, are mostly negative for the level of pension benefits. Hence, those who keep track of (possible) changes in the pension system (i.e., the higher educated) may reasonably expect lower benefits and a more uncertain future.

The expected replacement rate decreases with age until age 48, and uncertainty increases with age until age 36. Indeed, the current proposed changes in retirement income (increase in eligibility age, increasing premia) increases uncertainty for the young and decreases their income. Furthermore, uncertainty has been increasing during the last few years, with pension income expected to decrease. Marital status is not important, which is not surprising, since the differences between singles and couples are small for state pension benefits and nonexistent for occupational pensions. The uncertainties in pension benefits elaborated upon above (reforms, financial crisis) hold for both couples and singles, and hence there is no reason to expect significant differences between the two.

On the usefulness of the probabilistic survey questions, chapter 2 finds that researchers should be careful in using the answer to these questions. To be precise, the questions are difficult to answer for respondents with less knowledge of probabilities. As a result, around one third of the sample gives answers violating the laws of probability. Not surprisingly, education plays an important role: less educated individuals are more likely to violate the laws of probability. As these inconsistent answers are not usable in empirical work, the final sample consists of relatively high educated respondents. Ignoring endogenous sample selection due to incorrect responses to probabilistic survey questions concerning pension entitlements biases the results toward a more pessimistic expectation and excess uncertainty in the replacement rate.

1.4.2 Chapter 3

Chapter 3 first presents a theoretical lifecycle model with uncertainty in pension benefits, as well as uncertain lifespan. This model shows that uncertainty in pension benefits leads to a precautionary saving motive: compared to a model without uncertainty, savings are higher, in order to compensate for the possibility that pension benefits turn out to be lower than expected. Higher life expectancy also leads to higher savings, as individuals wish not to outlive their wealth in case they become very old. Next, I take the model to the data, and estimate the saving rate equation implied by the theoretical model using weighted quantile regression techniques. Quantile regressions are useful to allow the effects of, for instance, uncertainty to depend on the level of saving: those with higher rates of saving may well be different from those with low rates of saving. Moreover, based on a version of the lifecycle model with borrowing constraints, the theory predicts to observe differences between these groups. The weighting tries to correct for the sample selection effects found in chapter 2.

I find that richer, wealthier households replace private savings by expected pension benefits. That is, I find a significant crowding out effect using subjective expectations data. Precautionary savings against uncertainty in pension income and uncertainty in lifespan are confirmed for the more affluent households in the sample, that is, in the higher quantiles of the saving rate distribution. The results are in line with the lifecycle model with borrowing constrains and uncertainty in pension income.

1.4.3 Chapter 4

Regarding the factors explaining who owns annuity products and endowment policies, I find a clear socio-economic gradient between owners and non-owners: the results indicate that age, income and wealth are important determinants for ownership of annuities and endowments. Older, wealthier and richer households are more likely to purchase these insurance products. The annuity puzzle therefore mainly exists among the lower socio-economic classes of the Dutch population. Borrowing constraints or lack of financial literacy may keep this group from buying these insurance products.

Regarding measurement errors in observed ownership rates, I estimate the degree of underreporting annuity ownership to be around 32%-points, which is a considerable fraction of the population. Around 12% is estimated to report to own an annuity while the household does not. On the contrary, I do not find evidence of over- or underreporting ownership of endowment policies. These results suggest that the annuity puzzle is not as large as usually perceived; asymmetric measurement errors can partly explain the annuity puzzle.

1.4.4 Chapter 5

Regarding the usefulness of retrospective earnings information, chapter 5 shows that being able to calculate lifetime earnings is a major improvement if measurement errors are present in the data. Moreover, the study shows, by examining average earnings as well as the slope of the wage path by age, that the retrospective data reflect cross-country differences in earnings rather well. For instance, Polish and the Czech respondents are found to be considerably poorer on average compared to Dutch or Swedish households.

Regarding the size of the crowding out effect, I find that the estimated crowd-out is equal to 47.1% using robust regression and 60.9% using median regression techniques, and in both cases significantly different from zero and 100%. When using financial wealth as the dependent variable instead of net worth, the crowd-out is estimated to be between 77.8% and 87.0%. These results suggest that European households will react to reductions in pensions, for instance, due to pension reforms, by increasing private savings, although the savings reaction is not strong enough to fully compensate for the decline in pension benefits. As such, a reduction in pension benefits may cause some households to run down their private savings too soon after retiring, and to have to lower the standard of living subsequently. Moreover, I show that this is most likely to happen to lower educated individuals, and to Italian, Spanish and Greek households.

Chapter 2

Probabilistic Survey Questions and Incorrect Answers: Retirement Income Replacement Rates*

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* This chapter is based on Van Santen, Alessie and Kalwij (2012).

2.1 Introduction

The standard life–cycle consumption model with uncertain (pension) income predicts that consumption during one's working life is positively related to what individuals expect to receive as income, and negatively related to income uncertainty (Caballero, 1990). In most empirical work in economics (see e.g., Feldstein, 1974; Attanasio and Rohwedder, 2003; Kapteyn et al., 2005), individual-specific expectations and uncertainty are not available, leading authors to assume static, rational expectations. To avoid making such strict assumptions regarding the expectation formation process, several studies suggest using individuals' subjective expectations of future income (Dominitz and Manski, 2006; Guiso et al., ming). Of particular interest, and the ones used in this study, are probabilistic questions of the type suggested by Dominitz and Manski (1997) and Manski (2004) which allow the researcher to elicit the subjective cumulative distribution function of an individual's pension income. Manski (2004) provides an overview of the use of probabilistic questions, which have become increasingly popular in recent years and have been used to assess the likelihood of general events (such as inflation and social security benefits) as well as person–specific events (such as mortality and one's economic situation). Manski suggests two reasons why eliciting expectations in a probabilistic way is better than eliciting expectations from vaguely defined answer categories (e.g., an event is "very likely" or "not too likely"). First, the numerical scale allows comparisons among individuals. Second, the consistency of a respondent's answers can be checked using the laws of probability.

This article contributes to the empirical literature by investigating whether incorrect (or inconsistent) answers to probabilistic survey questions, and their subsequent removal from the sample, lead to endogenous sample selection. For example, less–educated and less financially literate persons may be less likely to answer such questions in a meaningful way—that is, their answers may not satisfy certain laws of probability—and may also have a different retirement income replacement rate. Simply excluding these observations when analyzing the determinants of the subjective replacement rate or subjective uncertainty, as is commonly done in other papers (e.g., Dominitz and Manski, 2006), can therefore result in endogenous sample selection and bias the parameter estimates.

The quality of subjective expectations, elicited using probabilistic survey questions, is examined in other papers.[1] Hurd and McGarry (1995, 2002) investigate the validity of subjective survival probabilities and find that individuals are well able to predict their own mortality, underlining Manski (2004)'s conclusion that probabilistic survey questions are informative. Dominitz (1998) shows that next–year income expectations are able to predict subsequent realizations reasonably well. In addition, data on expectations and subsequent realizations are used in Dominitz (2001); Das and van Soest (1997); Das and Donkers (1999); Stephens (2004). The overviews of Hurd (2009) and Pesaran and Weale (2006) also emphasize the predictive power of subjective probabilities.

However, Dominitz and Manski (1996,9) signal some evidence that not all respondents answer correctly. Dominitz and Manski (1996) use survey software that automatically signals mistakes in the probabilities entered by the respondent, after which the respondent must correct the mistake, but still allows the researcher to keep track of them. The authors find that 7% of respondents violate the monotonicity of answers, and 40% provide answers incompatible with the (previously elicited) median of the subjective distribution of future income. Dominitz and Manski (1997) report 21% item non–response, 8% providing constant probabilities over the thresholds, and 5% violating monotonicity. Kleinjans and van Soest (2010) show that two common fears associated with probabilistic questions, namely, non–response and focal points (e.g., answering 0%, 50%, or 100%), do not affect the determinants of retirement expectations, but that individuals round off probabilities instead. Manski and Molinari (2010) investigate the extent of rounding in more detail and find heterogeneity in answering patterns, with a small fraction (11% of the respondents) always rounding up to multiples of 50. We do not address the issues of rounding or focal points. More closely related to our study are Dominitz and Manski (2006), who compare the sample statistics of non–respondents to those in their final sample, using data from the Survey of Economic Expectations (SEE). Non–respondents, defined as providing either missing values, incomplete, non–

[1] See the April/May 2011 special issue in the Journal of Applied Econometrics for a collection of papers using subjective expectations.

valid, or unusable answers for estimating the subjective distribution, in the SEE are more likely to be female, less likely to be non–Hispanic whites, less likely to be labor force participants, less likely to be married, and less likely to be high school or college graduates. Furthermore, the probability of non–response is non–monotonic in age. The degree of non–response, Dominitz and Manski (2006) claim, compares favorably to that from the Health and Retirement Study, and hence the authors conclude that selection effects are not an issue. By contrast, our empirical findings provide strong evidence of endogenous sample selection effects when omitting incorrect answers from an analysis of expected retirement income replacement rates.

We use responses to the Dutch Pension Barometer survey, described in detail in Section 2.2, which follows the Dominitz and Manski (1997, 2006) approach. By eliciting points on the (subjective) distribution function of future pension income, these questions allow the researcher to compute estimates of the expected replacement rate, that is, the ratio of expected pension income to current income, as well as its standard deviation, which can be interpreted as uncertainty regarding the replacement rate. We find that about one–third of the respondents are unable to answer correctly, and that the incidence of violations correlates with observable background variables, such as education, income, and gender. De Bresser and van Soest (2010) find similar results using the same data source, but use only the sample with correct responses, thus implicitly assuming exogenous sample selection. A new finding is that excluding those individuals for whom it is not possible to compute the expectation or standard deviation of future pension income results in endogenous sample selection. The resulting biases are quantified by predicting both the expected replacement rate and the standard deviation of the replacement rate using a linear model without correcting for selection effects and using a Heckman model that does correct for possible endogenous selection effects. This quantification shows that ignoring endogenous sample selection yields a downward bias in the predicted expected replacement rate and an upward bias in the predicted uncertainty (standard deviation) of the replacement rate. These biases are largest for less–educated individuals.

The paper is organized as follows. Section 2.2 discusses the data and the exact wording of the survey questions. Section 2.3 examines the incidence of violations of the laws of probability and how it relates to individual characteristics. Section 2.4 discusses the computation of the expected value and standard deviation of the replacement rate and relates these to individual characteristics. It also quantifies the consequences for the parameter estimates of ignoring endogenous sample selection. Finally, Section 2.5 presents our conclusions.

2.2 Data

Since the summer of 2006, CentERdata has been collecting data on the pension benefit expectations of Dutch households with the Pension Barometer survey. CentERdata, affiliated with Tilburg University, specializes in data collection via (Internet) surveys and administers the Pension Barometer survey to members of their CentERpanel, a representative sample of the Dutch population aged 16 and above. Those without access to the Internet are provided with a set–top box for their television. The CentERpanel households are interviewed regularly about various subjects. In particular, the DNB Household Survey (DHS) is sent out to the same CentERpanel members. Hence, background information on household panel members is available from previous interviews, since unique identifiers for household members are available.

The Dutch pension system consists of three pillars. The first pillar is the flat–rate public pension, provided to all inhabitants aged 65 and above. In 2010, this amounted to €1057 gross for singles and €735 gross for married individuals. The second pillar, the occupational pensions, are mandatory for most employees, and both employers and employees contribute to a pension fund. Finally, the third pillar concerns private pension products, such as annuities bought from banks or insurers. This paper concerns pension benefit expectations from the first and second pillars together.

There are two versions of the Pension Barometer: a monthly survey and a yearly survey. The monthly survey has a rotating panel structure, such that each member receives the survey once every three months. The main focus is on expectations regarding the public pension (see Bissonnette and van Soest, 2010). The yearly survey is presented in two parts to the panel members, the first part in March and the second in June. The June version of the annual survey is our main source of information, for which the data for 2007, 2008, and 2009 are available. As only employees receive the probabilistic survey questions concerning the retirement income replacement rate, our analytical sample is restricted to employees.

We use the responses to the following sequence of questions to obtain a probability distribution of the replacement rate at two different retirement ages for each individual.

Question 2.1. *At what age do you think you can retire at the earliest, following your employer's pension scheme?*

The answer to this question, say, age Y, is used in the subsequent question:

Question 2.2. *If you would retire at age Y, please think about your total net pension income, including social security, compared to your current total net wage or salary. What do you think is the probability that the purchasing power of your total net pension income in the year following your retirement will be*

a)	*more than 100% of your current net wage?*	... %
b)	*less than 100% of your current net wage?*	... %
c)	*less than 90% of your current net wage?*	... %
d)	*less than 80% of your current net wage?*	... %
e)	*less than 70% of your current net wage?*	... %
f)	*less than 60% of your current net wage?*	... %
g)	*less than 50% of your current net wage?*	... %

Question 2.3. *Can your employer fire you for reaching a certain (pension eligibility) age?*

The answer can be either yes or no. If the respondent answers yes, a follow–up question is posed:

Question 2.4. *At what age is this?*

The answer to this question, say, age Z, is used in the next question. If, however, the respondent answered no to question 2.3, age Z is fixed to be either 65 if the answer to question 2.1, age Y, was lower than 55, or Y+5 years if Y was larger than

54. Hence, in question 2.5 respondents are shown a particular age that is higher than the age used in answering question 2.2. This age Z can be interpreted as their latest retirement age.

Question 2.5. *If you would retire at age Z, please think about your total net pension income, including social security, compared to your current total net wage or salary. What do you think is the probability that the purchasing power of your total net pension income in the year following your retirement will be*

a) *more than 100% of your current net wage?* ... %
b) *less than 100% of your current net wage?* ... %
⋮
g) *less than 50% of your current net wage?* ... %

These questions are intended to reveal the distribution of the net retirement income replacement rate of Dutch employees. Traditionally, the replacement rate has been defined as the ratio between pension income and income just prior to retirement. This question asks instead the net replacement rate compared to the current net wage, which better suits the average pay system presently in place in the Netherlands.[2] For the remainder of this paper, we will call this the replacement rate, or RR. Throughout this paper, the notation for the probability that, say, $RR > 100$ is $\mathbb{P}(RR > 100)$, as, for instance, asked in question 2.2a.

There is some evidence of item non–response for these questions, since some respondents answer questions 2.1 and/or 2.3 but not the probability questions. These are classified as "Don't know" in the remainder of this paper and concern 27 observations for Q2.2 and 35 observations for Q2.5. Table 2.1 shows sample statistics for each question in the three survey years. The number of observations varies between years, as well as between the two questions.

The DHS, formerly known as the VSB–CentER Savings Study, is a yearly survey that started in 1993 and covers about 2000 Dutch households, that also belong to

[2] Dominitz and Manski (2006) and Delavande and Rohwedder (2008) both elicit expectations on the *level* of retirement income, instead of the replacement rate. We believe that the replacement rate is a better measure for retirement income in the Netherlands, as most people at least know rules of thumb for computing the replacement rate (an increment of around 1.75% per year worked), but may be less knowledgable about the level of pension benefits.

Table 2.1. Response patterns[a]

Year	2007				2008				2009			
Variable	Earliest[b]		Latest		Earliest		Latest		Earliest		Latest	
Number of employees	574		574		445		445		459		459	
Don't know	9		15		8		9		10		11	
Retirement age	64	(63.3)	66	(66.6)	65	(63.3)	65	(66.7)	65	(63.8)	65	(66.9)
$\mathbb{P}(RR > 100)$	0	(11.8)	0	(21.5)	0	(9.6)	0	(19.0)	0	(11.0)	0	(21.2)
$\mathbb{P}(RR < 100)$	95	(69.1)	90	(64.5)	98	(68.6)	90	(66.2)	90	(67.9)	85	(65.1)
$\mathbb{P}(RR < 90)$	75	(61.0)	70	(55.8)	80	(61.2)	70	(55.6)	75	(59.5)	60	(54.2)
$\mathbb{P}(RR < 80)$	60	(53.8)	50	(44.6)	60	(53.7)	50	(46.5)	50	(51.6)	50	(45.0)
$\mathbb{P}(RR < 70)$	40	(39.5)	20	(30.6)	40	(40.0)	25	(31.9)	30	(37.4)	25	(31.8)
$\mathbb{P}(RR < 60)$	10	(25.1)	10	(19.5)	10	(24.8)	10	(20.5)	10	(22.7)	10	(19.4)
$\mathbb{P}(RR < 50)$	2	(17.6)	1	(14.2)	5	(15.0)	1	(14.1)	5	(15.0)	1	(13.6)
Observations	565		559		437		436		449		448	

[a] This table shows the cross–sectional median (mean) of each variable. The initial sample is restricted to non–missing explanatory variables in Table 2.2.

[b] Earliest refers to earliest retirement age, in questions 2.1 and 2.2, and latest refers to latest retirement age, in questions 2.3, 2.4, and 2.5.

the CentERpanel mentioned above. The survey is administered between February and December of the specific year. Respondents answer questions on a broad range of topics, including household income, assets and liabilities, health, and economic and psychological concepts (see Alessie et al., 2002 for an extended description). This study uses the three waves from 2007 to 2009 to obtain individual characteristics. In addition, and as will be explained in detail in Section 2.4, our analysis uses four variables that identify a Heckman selection model which takes into account possible endogenous sample selection. These four variables relate to the so–called exclusion restrictions that are imposed on the main equation of the Heckman selection model, i.e. these four variables are only included in the selection equation. We refer to these four variables as the excluding variables. To construct them, we consider the following questions from the Pension Barometer survey and the DHS that provide information on whether or not people are able to answer probabilistic questions and which are not related to retirement.

Question 2.6. *How likely is it that you will attain (at least) the age of* 65 / 75 / 80 *? Please indicate your answer on a scale of 0 through 10, where 0 means "no chance at all" and 10 means "absolutely certain".*

Respondents answer at most three but mostly two questions, depending on their actual age. The survival probability should be decreasing in age; surviving until age 75 implies survival up to age 65. We construct the variable *Survival probability error*, which is equal to one if the respondent violates monotonicity, and zero otherwise.

Question 2.7. *What is the probability that the purchasing power of your total household income, in one year from now, will be* higher / lower *than it is now?*

Respondents provide two probabilities, one for the higher expected income and one for the lower. We construct the variable *Expected income adding–up error*, which is equal to one if these probabilities sum up to more than 100%, and zero otherwise.

The next question first elicits the minimum and maximum expected household incomes, after which a series of four follow–up questions are posed based on those answers:

Question 2.8. *What do you think is the probability that the total net yearly income of your household will be less than* €$[LOWEST + (HIGHEST - LOWEST) * \{0.2/0.4/0.6/0.8\}]$ *in the next 12 months?*

In words, respondents are asked the probability that their net household yearly income will be less than 20% above their lowest expected income, and similarly for 40%, 60%, and 80% above. These four probabilities should be increasing with the threshold level (less than 20% above the lowest expected income implies less than 40% above the lowest expected income), and we construct the variable *Expected income probability error*, which is equal to one if this is violated, and zero otherwise. The final question has a setup similar to that of question 2.8 but concerns expected inflation, for which we construct the variable *Inflation probability error*, which is equal to one if monotonicity is violated, and zero otherwise.

Table 2.2 shows the mean and standard deviation of individual characteristics used in this study: Female (=1 if female), age, education dummies, partner (=1 if married or in a relationship), gross monthly income in euros, years worked (Experience), and the four excluding variables. For education, we divide respondents into Elementary, Secondary, College, and University educational attainment.

The sample consists of mostly males and married or cohabiting persons. Gross monthly income is around €2700. More than 42% of respondents have higher vocational or university education. As for the excluding variables, most errors are made due to violating monotonicity for expected income and inflation.

Table 2.2. Descriptive statistics explanatory variables[a]

Variable	2007		2008		2009	
Female	0.395	(0.489)	0.375	(0.485)	0.364	(0.482)
Single	0.258	(0.438)	0.243	(0.429	0.233	(0.423)
Income	2656.7	(1201.4)	2779.0	(1298.4)	2867.6	(1323.1)
Experience	20.373	(11.996)	21.251	(11.578)	22.480	(11.748)
Age	44.463	(10.028)	45.458	(10.061)	46.747	(9.998)
Elementary	0.240	(0.428)	0.236	(0.425)	0.235	(0.425)
Secondary	0.336	(0.473)	0.337	(0.473)	0.307	(0.462)
College	0.279	(0.449)	0.290	(0.454)	0.305	(0.461)
University	0.145	(0.352)	0.137	(0.344)	0.153	(0.360)
Survival probability error	0.007	(0.083)	0.002	(0.047)	0.007	(0.081)
Expected income adding–up error	0.057	(0.233)	0.054	(0.226)	0.037	(0.189)
Expected income probability error	0.171	(0.377)	0.155	(0.362)	0.198	(0.399)
Inflation probability error	0.145	(0.352)	0.294	(0.456)	0.338	(0.473)
Observations	574		445		459	

[a] Table shows the mean (standard deviation) of each explanatory variable for the sample of employees for which all dependent and explanatory variables are known.

2.3 Violations

Questions 2.2 and 2.5 ask respondents to fill in seven probabilities. This section checks the answers for consistency. Question 2.2a asks $\mathbb{P}(RR > 100)$; question 2.2b asks $\mathbb{P}(RR < 100)$. Since these events are mutually exclusive, the sum of the answers to these questions should not exceed 100% so as not to violate adding up. In order not to violate monotonicity, the answers to questions 2.2b to 2.2g should be non–increasing; if the replacement rate is less than 90% of the current income, it is, of course, also less than 100% of the current income. Table 2.1 shows that, for the average respondent, the answers to 2.2a and 2.2b add up to less than 100% and that, on average, there are no violations of monotonicity. Table 2.3 shows the number of individuals (by year) for whom the sum of their answers to questions 2.2a and 2.2b add up to more than 100% and/or who violate monotonicity in their answers to questions 2.2b to 2.2g. The percentage of correct responses was about 65% in 2007 and about 70% in 2008 and 2009, which suggests a slight decrease in the incidence of violations. Furthermore, there exists a clear pattern in the violations, in that for each year and each type of violation (i.e., six tests), we find a significant positive association (p=0.000) between correctly answering questions 2.2 and 2.5.

The number of Pension Barometer respondents violating monotonicity and/or adding up is considerably larger than for the SEE respondents, reported by Dominitz and Manski (1997): conditional upon answering preliminary questions con-

Table 2.3. Violations of the laws of probability[a]

			Panel A: 2007			
Replacement rate	Earliest retirement age (Q2.2)			Latest retirement age (Q2.5)		
	Monotonicity			**Monotonicity**		
Adding up	Correct	Incorrect	Total	Correct	Incorrect	Total
Correct	367	143	510	379	102	481
Incorrect	45	19	64	71	22	93
Total	412	162	574	450	124	574
			Panel B: 2008			
Replacement rate	Earliest retirement age (Q2.2)			Latest retirement age (Q2.5)		
	Monotonicity			**Monotonicity**		
Adding up	Correct	Incorrect	Total	Correct	Incorrect	Total
Correct	310	93	403	314	74	388
Incorrect	29	13	42	45	12	57
Total	339	106	445	359	86	445
			Panel C: 2009			
Replacement rate	Earliest retirement age (Q2.2)			Latest retirement age (Q2.5)		
	Monotonicity			**Monotonicity**		
Adding up	Correct	Incorrect	Total	Correct	Incorrect	Total
Correct	320	107	427	322	74	396
Incorrect	19	13	32	47	16	63
Total	339	120	459	369	90	459

[a] Table shows the number of respondents that violate adding up ($\mathbb{P}(RR > 100) + \mathbb{P}(RR < 100) > 1$), violate monotonicity ($\mathbb{P}(RR < 100) > \mathbb{P}(RR < 90)$or similar for other thresholds), violate both or answer correctly, in each year and for both questions 2.2 and 2.5

cerning lowest and highest expected incomes, and conditional on providing probabilities that vary with the threshold, 5% of SEE respondents are unable to report correct probabilities concerning next–year income. For pension benefit expectations elicited from SEE respondents, studied in Dominitz and Manski (2006), no information is given regarding the number of inconsistent responses. The main difference between the survey data we use and the SEE survey data is the fact that inconsistencies are ruled out in advance in the latter case. That is, the respondent is requested to review the answer in case of a violation of monotonicity. Hence, in the final data, there are no inconsistencies in Dominitz and Manski (2006). Whether or not these requests to review the answer ultimately lead to a larger sample, as well as to more informative answers, remains an open question for future research. To further explain the difference in the number of violations, we note that SEE respondents are always asked to provide probabilities of income being *less than* the thresholds, and therefore never violate adding–up, by definition. Second, probabilities are asked about income being less than four thresholds, while our question has seven thresholds. Hence, there are more possibilities to make mistakes in our question. For the Health and Retirement Study (HRS), Delavande and Rohwedder (2008) report a loss in sample size of around 20% due to inconsistencies, when eliciting expectations of social security benefits from non–retirees under the age of 72.

2.3.1 Explaining the ability to answer correctly

This section examines the extent to which the ability to answer probabilistic questions correctly—that is, without violations of adding up or monotonicity—is related to individual characteristics. We use gender, age, education, household income and marital status as the explanatory individual characteristics. In addition, since the incidence of violations is lower in 2008 and 2009 compared to 2007 (see Table 2.3), we include a learning variable that equals one if the respondent is answering these questions for the first time, two if for the second time, and three if for the third time. For both questions separately, we define the variable *Able* to indicate the ability to answer correctly, where $Able_i = 0$ if respondent i violates adding up and/or monotonicity or is classified as "Don't know".

Table 2.4 reports the effects of individual characteristics on the ability to answer correctly (*Able*). We estimate (pooled) probit models with time–specific intercepts. Table 2.4 reports parameter estimates, standard errors clustered at the individual level, and marginal effects.

First, we observe that the parameter estimates and significance levels are stable across the questions. We observe that older people are less likely to produce inconsistent answers, but the effect is not significant. Education is very important in explaining ability: Persons with a secondary, college, or university background are significantly less likely to make mistakes than the benchmark group with the lowest level of education. Jointly, the education dummies are highly significant (*p*-value = 0.000). A perhaps counterintuitive finding is that higher–income individuals are more likely to make mistakes, but the effect is not significant; the education dummies make the inclusion of income redundant, since more educated persons have higher incomes.[3] Women are more likely to violate, while marital status is insignificant. We will use the incidences of incorrectly answering the probabilistic

[3] Estimates without education dummies reveal that income has a significantly positive effect on the ability to answer correctly (not reported, but available upon request).

Table 2.4. Explaining violations[a]

Dependent variable: Able[b]	At the earliest retirement age (Q2.2)			At the latest retirement age (Q2.5)		
Covariates	Parameter estimate	Standard error	Marginal effect	Parameter estimate	Standard error	Marginal effect
Age	0.050	(0.035)	-0.001	0.026	(0.036)	0.001
Age^2	-0.001	(0.0004)		-0.0003	(0.0004)	
Secondary	0.146	(0.105)	0.050	0.223**	(0.107)	0.074**
College	0.441***	(0.113)	0.146	0.451***	(0.112)	0.145
University	0.705***	(0.154)	0.209	0.686***	(0.151)	0.198
log Income	-0.040	(0.099)	-0.014	-0.105	(0.101)	-0.036
Female	-0.117	(0.093)	-0.041	-0.232**	(0.094)	-0.081
Single	0.044	(0.093)	0.015	0.047	(0.095)	0.016
Experience	0.002	(0.005)	0.001	0.0002	(0.005)	0.000
Survival probability error	0.222	(0.489)	0.073	0.571	(0.584)	0.160
Expected income adding-up error	-0.197	(0.171)	-0.072	-0.391**	(0.158)	-0.144
Expected income probability error	-0.327***	(0.095)	-0.120	-0.263***	(0.093)	-0.094
Inflation probability error	-0.229***	(0.080)	-0.082	-0.125	(0.081)	-0.043
Learning	0.051	(0.049)	0.018	0.038	(0.049)	0.013
Dummy 2008	0.191**	(0.083)	0.066	0.127	(0.082)	0.043
Dummy 2009	0.210**	(0.084)	0.072	0.121	(0.086)	0.041
Constant	-0.609	(1.071)		0.466	(1.091)	
Observations		1451			1443	
Pseudo-R^2		0.046			0.037	
log L		-860.4			-844.9	
p-value Wald test model		0.000			0.000	
p-value Wald test Age		0.326			0.724	
p-value Wald test Education		0.000			0.000	
p-value Wald test Income		0.281			0.114	
p-value Wald test Excluding variables		0.000			0.001	
p-value Wald test Time dummies		0.017			0.224	
p-value Chow test		0.672			0.959	

[a] Table shows parameter estimates, standard errors clustered at the respondent level, and marginal effects after probit. Here ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

[b] The dependent variable *Able* equals one if the respondent answers correctly, and zero if the probabilities violate adding up and/or monotonicity or the answer is classified as "Don't know".

questions corresponding to the survival probability, income expectation, and inflation expectation as excluding variables in the Heckman selection model in Section 2.4 to explain the expected replacement rate and the standard deviation of the replacement rate. The bottom of Table 2.4 shows that these excluding variables are jointly significant. Those individuals who make errors in these other probabilistic questions are more prone to make mistakes in the probabilistic questions concerning the replacement rate. Time effects show that significantly fewer people made mistakes in 2008 and 2009, yet this cannot be attributed to learning effects, which have an insignificant impact. We have no ready explanation for this finding. A Chow test for structural breaks shows that the coefficients, other than the intercept, are stable over time; the null hypothesis of time–invariant slope parameters cannot be rejected (see the bottom of Table 2.4).

The results we obtain are in line with the results found in Gouret and Hollard (2011), albeit on a different aspect of probabilistic survey questions. Gouret and Hollard study expectations of risk and return of an investment of $ 1000 in a stock mutual fund, using similar probabilistic survey questions to those used in our study. Moreover, Gouret and Hollard (2011) derive a measure of coherence, to study whether the elicited probabilities are similar in magnitude to those obtained from a differently phrased question on the same subject (i.e. whether there is a framing effect à la Tversky and Kahneman (1974)). Gouret and Hollard (2011) find that high–educated respondents are more coherent, as are men. A minor difference is the fact that Gouret and Hollard find a stronger income effect, with higher–income respondents (except for the most affluent) providing more coherent answers. Similarly, Dominitz and Manski (1997) have reported a higher effective response rate for university graduates, being 36% more likely to be in the final sample compared to those with 12 years of schooling or less. Delavande and Rohwedder (2008) report statistically significant differences in education, an index of probabilistic thinking, and wealth between the consistent and inconsistent groups of respondents in the HRS.

2.4 Replacement rates

This section first computes the expected value and variance of the replacement rate. Second, it analyzes the determinants of the expected replacement rate and uncertainty (the standard deviation of the replacement rate) and relates these to individual characteristics using Heckman selection models that take into account possibly endogenous sample selection (Heckman, 1979). Finally, we quantify the selection bias by predicting the expected value and standard deviation of the replacement rate with and without sample selection corrections for different types of individuals.

2.4.1 Computation

Dominitz and Manski (1997), Manski (2004), and De Bresser and van Soest (2010) fit a log–normal distribution to the probabilities. This parametric approach relaxes the need to consider small violations in adding up or monotonicity. However, this approach has disadvantages as well. First, it is not clear why the replacement rate should be log–normally distributed. Second, the probabilities need to vary with the threshold to make a non–linear least squares estimation feasible. Third, if the violation becomes "too large", the non–linear least squares estimates hardly converge, leading to implausible estimates of location and spread of the replacement rates. Yet, what exactly is too large is not at all clear. Therefore, we propose a nonparametric distribution of the replacement rate.

The answers to questions 2.2 and 2.5 provide information on the subjective cumulative distribution function for each respondent. There are seven thresholds for which we know the probability that the replacement rate is lower or higher than this threshold. We assume a nonparametric, piecewise–linear subjective distribution function for each respondent; that is, the distribution function is uniform between two thresholds. The CDF, denoted $F(RR)$, can then be written as

$$F(RR) = \begin{cases} \mathbb{P}(RR < 50)\left(\frac{RR}{50}\right) & \text{if} \quad 0 \leq RR < 50 \\ \mathbb{P}(RR < 50) + \mathbb{P}(50 \leq RR < 60)\left(\frac{RR-50}{10}\right) & \text{if} \quad 50 \leq RR < 60 \\ \mathbb{P}(RR < 60) + \mathbb{P}(60 \leq RR < 70)\left(\frac{RR-60}{10}\right) & \text{if} \quad 60 \leq RR < 70 \\ \mathbb{P}(RR < 70) + \mathbb{P}(70 \leq RR < 80)\left(\frac{RR-70}{10}\right) & \text{if} \quad 70 \leq RR < 80 \\ \mathbb{P}(RR < 80) + \mathbb{P}(80 \leq RR < 90)\left(\frac{RR-80}{10}\right) & \text{if} \quad 80 \leq RR < 90 \\ \mathbb{P}(RR < 90) + \mathbb{P}(90 \leq RR < 100)\left(\frac{RR-90}{10}\right) & \text{if} \quad 90 \leq RR < 100 \\ \mathbb{P}(RR < 100) + \mathbb{P}(RR = 100) & \text{if} \quad RR = 100 \\ \mathbb{P}(RR \leq 100) + \mathbb{P}(100 < RR < 120)\left(\frac{RR-100}{20}\right) & \text{if} \quad 100 < RR < 120 \end{cases} \tag{2.1}$$

All the probabilities are known from the answers given by respondents. Writing the CDF as above allows us to work with a continuous distribution function. There is also one discrete element, since the answers to questions 2.2a and 2.2b can add up to less than 100%, which indicates that there is a positive probability associated with the event that the retirement income is exactly equal to the current income. We fix the upper bound of the distribution function (arbitrarily) at 120%, and the lower bound at 0%. These choices influence the value of the computed replacement rate but do not induce additional cross–sectional variation and, therefore, do not influence the results of the empirical analysis.

To compute the expected replacement rate, we use the CDF to find the probability density function $f(RR)$ by differentiation. The expected value equals

$$E(RR) = \int_0^{120} RRf(RR)\, dRR \tag{2.2}$$

The measure for pension income uncertainty is the standard deviation of the replacement rate. Again, we use the CDF to find $E(RR^2) = \int_0^{120} RR^2 f(RR)\, dRR$ and, compute

$$\text{SD}(RR) = \sqrt{E\left(RR^2\right) - \left(E(RR)\right)^2} \tag{2.3}$$

The standard deviation is set to zero if the response jumps from 100% to 0% for two consecutive thresholds, as this corresponds to the least uncertainty in the replacement rate a respondent can express.

Table 2.5 shows summary statistics for the expected value and standard deviation of the replacement rate. Since these cannot be computed for respondents violating the laws of probability, the samples are smaller than those used for Table 2.4. The differences between the years are small, although we observe a slightly lower replacement rate in 2008. We see a large variation in the expected replacement rate, between 25% (which is the minimum due to the lower bound assumption) and 110% (the maximum) of the current income, with an average of 75%. Furthermore, uncertainty about pension entitlements varies greatly in the sample. On average, respondents have a standard deviation of about 15%, but this varies between 0% and 43.9% of the current income. The expected replacement rate is higher if the respondent faces question 2.5 with a higher retirement age. A back–of–the–envelope calculation shows that, on average, employees expect 1.67% more pension income for each additional year of employment (5% for a retirement delayed, on average, by three years; see Table 2.1). In addition, uncertainty is lower at this later retirement age. Figure 2.1 shows the empirical distribution of the expected value and standard deviation of the replacement rates, both as a histogram and as a kernel–smoothed estimate of the density (with a bandwidth of 9). The expected replacement rates (Figures 2.1a and 2.1c) are symmetrically distributed, with outliers in both tails. The median is around 70% of the current income. Figures 2.1b and 2.1d show a spike at a standard deviation of zero. These individuals have expressed to be certain about the level of the replacement rate. Compared to the other (uncertain) respondents[4], they have, on average, a significantly higher expected replacement rate. Moreover, they are three years older, are slightly less educated, and have similar monthly incomes; women and individuals with a partner express certainty more often. None of these differences in background characteristics are significant at conventional levels of significance.

2.4.2 Explaining expected value and standard deviation

Next, we examine the determinants of the expected value and standard deviation of the replacement rate for both questions by estimating Heckman selection mod-

[4] For brevity, these results are not displayed numerically.

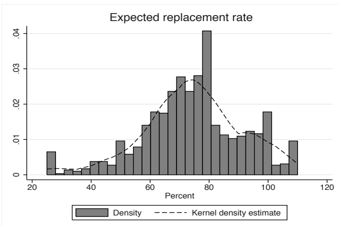
Table 2.5. Replacement rate summary statistics[a]

	At the earliest retirement age (Q2.2)					At the latest retirement age (Q2.5)				
Variable	Mean	Std. Dev.	Min.	Max.	N	Mean	Std. Dev.	Min.	Max.	N
Panel A: 2007										
$E(RR)$	75.2	16.8	25	110	367	80.6	17.4	25	110	379
$SD(RR)$	14.5	8.9	0	43.9	367	14.6	9.3	0	43.9	379
Panel B: 2008										
$E(RR)$	73.3	17.7	25	110	310	78.9	18.7	25	110	314
$SD(RR)$	15.6	9.8	0	43.9	310	14.9	10.0	0	43.9	314
Panel C: 2009										
$E(RR)$	75.0	17.0	25	110	320	80.1	17.7	25	110	322
$SD(RR)$	15.6	9.9	0	43.9	320	14.9	10.2	0	43.9	322

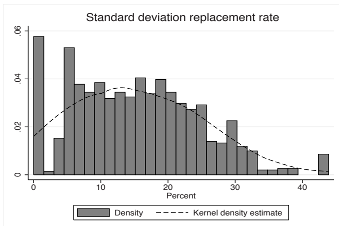
[a] Table shows the (cross–sectional) sample statistics for the expected replacement rate ($E(RR)$), computed according to equation 2.2, and the standard deviation of the replacement rate ($SD(RR)$), using equation 2.3, in each year for both questions 2.2 and 2.5

Figure 2.1. Expected value and standard deviation replacement rates

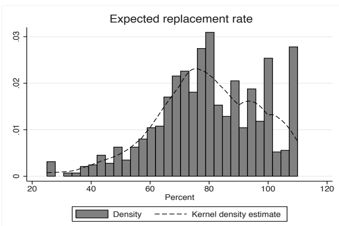
(a) Earliest retirement age



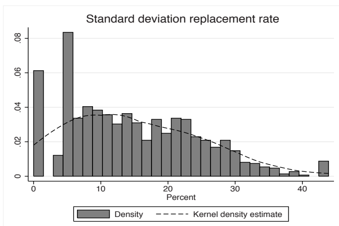
(b) Earliest retirement age



(c) Latest retirement age



(d) Latest retirement age



els (Heckman, 1979). The Heckman selection model consists of two equations. The first equation is a selection equation to determine who is able to answer probabilistic questions correctly (see Section 2.3.1). The second equation is an outcome equation in which the expected replacement rate or the standard deviation of the replacement rate is explained. The error terms of these two equations are assumed to be bivariate normally distributed with correlation coefficient ρ (see, e.g., Cameron and Trivedi (2005) for more details). Both equations are estimated simultaneously by the maximum likelihood (ML) method. For the Heckman (1979) two–step estimator, the results of the (probit) selection equation are exactly equal to those in Table 2.4. For maximum likelihood, the results are quantitatively and qualitatively similar and are therefore omitted here. We opt for ML to be able to cluster standard errors at the individual level.[5]

We use time effects, age, gender, marital status, education, income, and years of work experience as explanatory variables. Other specifications, in particular including the expected retirement age from questions 2.1 and 2.4, more flexible functions of income and several interaction effects, do not influence these results. The estimation results of the selection equation are already reported in Table 2.4. As discussed earlier, the exclusion restrictions are on the variables *Survival probability error*, *Expected income adding–up error*, *Expected income probability error*, and *Inflation probability error*. We assume, after controlling for incorrectly answering the replacement rate probabilistic questions, that these variables only affect the outcome variables through the selection adjustment and have no independent impact on the outcome variables. We believe this is a reasonable assumption, since these variables are solely related to the ability to answer probabilistic questions, and not to retirement income expectations. As discussed in Section 2.3.1 and again reported in Table 2.6 for the sample selection model, the excluding variables are jointly significant in explaining the ability to answer probabilistic survey questions correctly.

The estimation results of the outcome equations for the expected value and standard deviation of the replacement rate are displayed in Table 2.6 (for both questions). Standard errors are clustered at the individual level. For comparison, Table

[5] We use the `heckman` command in Stata 10.

2.6 also shows the results of estimating a linear model for the outcome equations by OLS, that is, without the endogenous sample selection correction.

The validity of the estimation results of the outcome equations depends on the assumptions underlying the sample selection model. The assumption of the bivariate normality of the errors of the selection and outcome equation is testable using the approach suggested by Lee (1984) and Pagan and Vella (1989).[6] More important than departures from bivariate normality is the validity of the exclusion restrictions, which is not testable. Obviously, if the exclusion restrictions are not valid, the Heckman results presented below are biased. Note that our explanatory variables in the outcome equation can be seen as a proxy for permanent income, in the style of the canonical lifecycle model. The only way in which pension income could be affected by the errors made in other probabilistic questions is when our excluding variables are a proxy for ability, i.e. the classic ability bias. Due to not observing ability, our proxy for permanent income (education, age, income, gender) may be correlated with the error term. To overcome this omitted variable bias, we have added a measure of financial literacy to both the selection and outcome equations. The measure of financial literacy is the same as used in Alessie et al. (2011a).[7] While financial literacy is marginally significant for explaining the expected replacement rate of question 2, it is generally insignificant in determining who answers correctly, as well as explaining the expected replacement rate and the standard deviation of the replacement rate. For brevity, these results are not reported but available upon request; the results reported in Table 2.6 are virtually unchanged. We do not believe

[6] The normality of the errors of the (probit) selection equation is tested by means of a Lagrange Multiplier test. We regress a vector of ones on the fitted values multiplied by the generalized residual, as well as the squared and cubed fitted values multiplied by the generalized residuals, and compute $n \cdot R^2$; the bottom of Table 2.6 shows that the null of normality is not rejected (p=0.655 and p=0.273 for the two questions, respectively). The key to testing bivariate normality is that, under the null hypothesis of bivariate normality, the error term of the outcome equation is a linear function of the error term of the selection equation. Pagan and Vella (1989) suggest adding fitted values of the selection equation multiplied by the inverse Mills ratio and the second and third powers of the fitted values, again multiplied by the inverse Mills ratio, to the outcome equation. Bivariate normality implies that the coefficients of these added variables equals zero. The p-value of a Wald test for this implication is presented at the bottom of Table 2.6. The results show that the null hypothesis of normality is not rejected at the 5% significance level.

[7] Specifically, the questions elicit knowledge of the concepts of interest compounding and money illusion. In our sample, 85% answers both questions correctly. We have included an indicator for answering both questions correctly, with the base group consisting of respondents answering one or both questions incorrectly, refuses to answer or gives a “Don’t know” answer. Other measures of financial literacy give similar results.

that unobserved ability biases our results.

Table 2.6. Estimation results of Heckman and linear models[a]

	Expected replacement rates			
	E(RR) Q2.2		E(RR) Q2.5	
Model	Heckman	Linear	Heckman	Linear
Age	-2.103***	-1.544**	-1.435*	-1.100
	(0.702)	(0.623)	(0.749)	(0.670)
Age^2	0.021***	0.015**	0.016**	0.013*
	(0.008)	(0.007)	(0.008)	(0.007)
Secondary	-7.357***	-5.719***	-7.642***	-5.525***
	(2.249)	(1.972)	(2.208)	(1.873)
College	-12.29***	-8.067***	-12.71***	-8.449***
	(2.351)	(1.965)	(2.369)	(1.950)
University	-13.18***	-7.152***	-12.31***	-6.415**
	(3.086)	(2.742)	(3.035)	(2.653)
log Income	-1.813	-1.870	-0.065	-0.720
	(1.878)	(1.638)	(1.943)	(1.680)
Female	-2.839*	-3.694**	-1.227	-3.409**
	(1.661)	(1.491)	(1.801)	(1.598)
Single	-0.985	-0.436	-2.141	-1.501
	(1.736)	(1.585)	(1.726)	(1.536)
Experience	-0.008	0.020	0.006	0.010
	(0.100)	(0.095)	(0.096)	(0.087)
Year 2008	-3.055**	-1.815	-2.802**	-1.898
	(1.281)	(1.121)	(1.382)	(1.166)
Year 2009	-1.154	0.0523	-1.652	-0.916
	(1.340)	(1.161)	(1.384)	(1.162)
Constant	157.5***	134.0***	130.4***	115.4***
	(21.21)	(18.58)	(21.84)	(19.75)
Observations	1451	997	1443	1015
log L	-5072	-4220	-5174	-4340
p-value Equation	0.000	0.000	0.000	0.000
p-value Age	0.004	0.010	0.143	0.187
p-value Education	0.000	0.0001	0.000	0.000
p-value Time dummies	0.054	0.175	0.120	0.265
ρ	-0.823		-0.875	
p-value $\rho = 0$	0.000		0.000	
p-value Exclusion restr.	0.000		0.029	
p-val. Normality selection [b]	0.655		0.273	
p-val. Normality outcome [c]	0.279		0.061	

Continued on next page

Table 2.6 – continued from previous page

	Standard deviation replacement rates			
	SD(RR) Q2.2		SD(RR) Q2.5	
Model	Heckman	Linear	Heckman	Linear
Age	1.016***	0.744**	0.515	0.323
	(0.383)	(0.326)	(0.412)	(0.359)
Age^2	-0.014***	-0.011***	-0.008*	-0.007*
	(0.004)	(0.004)	(0.005)	(0.004)
Secondary	4.021***	2.920***	4.147***	2.554**
	(1.249)	(1.119)	(1.218)	(1.068)
College	4.834***	2.178**	5.176***	2.186**
	(1.289)	(1.099)	(1.211)	(1.051)
University	7.318***	3.592***	6.452***	2.269*
	(1.582)	(1.372)	(1.559)	(1.351)
log Income	-0.577	-0.697	-0.506	-0.250
	(0.940)	(0.818)	(0.973)	(0.777)
Female	-1.086	-0.645	-1.205	0.201
	(0.921)	(0.813)	(0.996)	(0.835)
Single	0.051	-0.359	0.345	-0.035
	(0.888)	(0.795)	(0.933)	(0.808)
Experience	-0.015	-0.021	-0.034	-0.029
	(0.049)	(0.044)	(0.051)	(0.045)
Year 2008	2.098***	1.460**	1.042	0.564
	(0.735)	(0.611)	(0.786)	(0.627)
Year 2009	2.361***	1.755***	1.412*	1.091*
	(0.754)	(0.615)	(0.808)	(0.641)
Constant	-5.304	9.142	3.562	14.90
	(11.66)	(9.726)	(11.89)	(10.09)
Observations	1451	997	1443	1015
log L	-4433	-3582	-4503	-3687
p-value Equation	0.000	0.000	0.000	0.000
p-value Age	0.000	0.000	0.000	0.000
p-value Education	0.000	0.034	0.000	0.107
p-value Time dummies	0.003	0.010	0.181	0.235
ρ	0.896		0.965	
p-value $\rho = 0$	0.000		0.000	
p-value Exclusion restr.	0.004		0.003	
p-val. Normality selection [b]	0.655		0.273	
p-val. Normality outcome [c]	0.056		0.058	

[a] Heckman models are fitted in one step by the maximum likelihood method. The results of the selection equation are comparable to those of Table 2.4.

Clustered standard errors in parentheses. Here ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

[b] The normality assumption of the probit error terms is tested by means of the Lagrange multiplier test for detecting skewness and excess kurtosis (see the text for details).

[c] The normality of the outcome equation error term is tested by means of the procedure suggested in Pagan and Vella (1989) (see the text for details).

The selection and outcome equations are not independent: The correlation between the error terms, ρ, is significant for all four models. The negative sign of $\hat{\rho}$ in the expected replacement rate equations implies that unobservable factors that positively correlate with the probability of answering correctly, relate negatively with the expected value of the replacement rate. Furthermore, these unobservable factors are positively correlated with the uncertainty in the replacement rate (a positive $\hat{\rho}$ in the SD(RR) models). These significant correlation coefficients imply that biased parameter estimates are obtained from OLS models explaining the expected value or standard deviation of the replacement rate. Ignoring these sample selection effects would underestimate the strength of the education gradient, that is, the OLS estimates are overestimated in the model explaining the expected replacement rate, and underestimated in the model explaining the standard deviation of the replacement rate. A similar bias occurs for the time effects. This is important if these parameters are, for example, used to predict expected replacement rates and pension risk for explaining household consumption or savings behavior (Bottazzi et al., 2006; Van der Wiel, 2008; Guiso et al., ming).

Table 2.6 shows that, compared to less–educated individuals, higher–educated individuals expect a significantly lower replacement rate and are more uncertain about it. Two (possibly reinforcing) explanations for this finding are as follows. First, since higher–educated individuals, on average, earn higher wages, while the Dutch state pension system is redistributive in nature, they should expect a lower replacement rate than less–educated individuals. Furthermore, supported by the surprising fact that past work experience is not significant, the career path of higher–educated individuals is usually steeper and surrounded by greater uncertainty, making it harder to predict pension benefits, resulting in more subjective uncertainty. Second, these findings may reflect the fact that higher–educated individuals are better informed about their future pension entitlements by, for instance, keeping closer track of news and developments regarding their pension income. The recent turmoil on the financial markets following the credit crunch of 2008 affected both state and occupational pensions in the Netherlands, lowering pension benefits and increasing the eligibility age. Furthermore, recently implemented changes, including the change from final–pay to average–pay occupational pensions and the abolishment of tax–favorable early retirement contributions, are mostly negative for the level of pension benefits. Hence, those who keep track of (possible) changes in the pension system (i.e., the higher educated) may reasonably expect lower benefits and a more uncertain future.

The expected replacement rate decreases with age until age 48 (45) for the early (late) retirement age, and uncertainty increases with age until age 36 (31). Indeed, the current proposed changes in retirement income (increase in eligibility age, increasing premia) increases uncertainty for the young and decreases their income. Furthermore, uncertainty increases over time, with pension income expected to decrease. Income is not significant, due to both the inclusion of education dummies and the strong correlation between income and education, as well as the fact that the respondents are asked to condition on current income in answering the probabilistic questions. Marital status is not significant, which is not surprising, since the differences between singles and couples are small for state pension benefits and nonexistent for occupational pensions. The uncertainties in pension benefits elaborated upon above (reforms, financial crisis) hold for both couples and singles, and hence there is no reason to expect significant differences between the two.

To gain more insight in the magnitude of the selection bias, we predict both $E(RR)$ and $SD(RR)$ using the Heckman model and the linear model. We consider a benchmark individual who is a married, 50 year old male with 25 years of experience and a university degree. His gross income is €3000 per month, which is in between the median and mean incomes in our sample. Furthermore, we show the effects of changing one of these characteristics, as well as plug in sample averages for all the characteristics from Table 2.2. The survey year is 2008, and the results are shown in Table 2.7 below.

We see that the bias is quite substantial for the benchmark individual: about 4 percentage points for the expected replacement rate and about 2.5 percentage points for the standard deviation. The differences in the predictions are similar whether we consider earliest retirement (Q2.2) or latest retirement (Q2.5). The bias increases dramatically if we lower the education level: more than 10 percentage points for $E(RR)$ and more than six percentage points for $SD(RR)$. For the sample averages, the bias is larger than the benchmark as well: more than 7.5 percentage points for $E(RR)$ and more than five points for $SD(R)$. In all cases, the linear model underestimates the predicted expected replacement rate and overestimates the degree of uncertainty. To summarize, ignoring endogenous sample selection due to incorrect responses to probabilistic survey questions concerning pension entitlements biases the results toward a more pessimistic expectation and excess

Table 2.7. Heckman model versus linear model predictions[a]

Person	E(RR) Q2		E(RR) Q5		SD(RR) Q2		SD(RR) Q5	
Model	Heckman	Linear	Heckman	Linear	Heckman	Linear	Heckman	Linear
Benchmark[b]	74.90	70.92	83.66	78.73	14.22	16.75	11.47	14.26
	(2.36)	(2.23)	(2.64)	(2.32)	(1.27)	(1.08)	(1.34)	(1.16)
Age 40	76.76	72.64	83.36	78.06	17.06	19.80	14.02	17.39
	(2.31)	(2.19)	(2.64)	(2.35)	(1.28)	(1.06)	(1.34)	(1.17)
Age 60	77.32	72.20	87.19	81.97	8.53	11.43	7.29	9.77
	(2.71)	(2.58)	(2.95)	(2.56)	(1.42)	(1.21)	(1.46)	(1.22)
Elementary education	88.07	78.07	95.97	85.14	6.91	13.16	5.02	11.99
	(2.31)	(1.81)	(2.49)	(1.73)	(1.43)	(1.05)	(1.18)	(0.99)
Secondary education	80.72	72.35	88.33	79.62	10.93	16.08	9.17	14.54
	(1.90)	(1.58)	(2.15)	(1.62)	(1.17)	(0.84)	(1.05)	(0.88)
College education	75.79	70.00	83.26	76.69	11.74	15.34	10.20	14.17
	(1.68)	(1.43)	(2.01)	(1.58)	(1.00)	(0.79)	(1.00)	(0.84)
Single	73.91	70.48	81.51	77.23	14.28	16.40	11.82	14.22
	(2.70)	(2.65)	(2.86)	(2.55)	(1.39)	(1.21)	(1.45)	(1.27)
Female	72.06	67.22	82.43	75.32	13.14	16.11	10.27	14.46
	(2.45)	(2.27)	(2.80)	(2.40)	(1.44)	(1.20)	(1.47)	(1.27)
Income €1800	75.80	71.85	83.69	79.09	14.51	17.10	11.72	14.38
	(2.79)	(2.58)	(3.07)	(2.70)	(1.48)	(1.28)	(1.58)	(1.34)
Sample average[c]	79.12	71.69	86.54	77.68	11.83	16.49	9.66	15.35
	(1.51)	(1.20)	(1.84)	(1.23)	(1.02)	(0.66)	(0.89)	(0.69)

[a] This table shows the predicted values of the expected replacement rate ($E(RR)$) and the standard deviation ($SD(RR)$) from the estimated Heckman and linear models (see Table 2.6). Standard errors are in parentheses.

[b] The benchmark individual is a 50 year old married male with a university degree and 25 years of work experience who earns €3000 gross per month. The survey year is 2008. The other rows show the only deviation from this benchmark.

[c] The sample averages correspond to the 2008 column in Table 2.2.

uncertainty in the replacement rate.

2.5 Discussion and concluding remarks

This paper has been the first to quantify the selection bias due to incorrectly answering probabilistic survey questions concerning pension entitlements in a sample of Dutch employees. Given the mentioned selected samples reported in Dominitz and Manski (1997, 2006) and Delavande and Rohwedder (2008), a similar bias is likely to be found in other datasets, obtained from different respondents using different methods of interview and on different topics.

Two related questions arise: Do respondents have a correct estimation of the replacement rate, or should we keep assuming rational expectations in empirical work? More interesting, once the selection bias is controlled for, is the gap between subjective and objective replacement rates bigger or smaller? Knowing an individual's true replacement rate is notoriously difficult, and hence we resort to aggregate statistics, taken from administrative data collected by the Central Bureau of Statistics of The Netherlands. Table 2.8 reports replacement rates by gender and immigrant status, where the latter serves as a proxy for education. The first observation from this table is the fact that women have higher replacement rates than men. In table 2.6, we have seen a strong negative effect of being female on the expected replacement rate, if we do not control for endogenous sample selection. Controlling for selection, the significance of this negative effect disappears, suggesting that the selection–correction pushes the replacement rates towards the objective replacement rate. The second observation we make is that non–western immigrants (as a proxy for the less educated) have a much higher replacement rate, on average 14% higher, compared to both non–immigrants and western immigrants. A similar difference is obtained in Table 2.7, where the difference between predicted replacement rates for the sample average and the elementary educated equals 8% for the earliest retirement age, and 10% for the latest retirement age. Using a linear model, the differences are 6% and 8%, respectively. This supports the hypothesis that the selection correction yields more plausible results compared to using a linear model without selection correction. Moreover, this comparison shows that the elicited expectations are, on average, plausible, and should provide better results in empirical analysis than using strong rationality assumptions.

Table 2.8. Aggregate replacement rates (%)[a]

	Non–Immigrants	Immigrants	Western Immigrants	Non–Western Immigrants
Total	75	79	73	88
Male	66	71	64	79
Female	94	93	87	101

[a] This table shows the aggregate replacement rate by gender and immigrant status, as reported by Statistics Netherlands.

Future research should be devoted to prevent a reduction in sample size and a selected sample by using alternative ways of eliciting expectations. A first step has been taken by Delavande and Rohwedder (2008), using a visual format for eliciting the distribution of social security benefits. Delavande and Rohwedder obtain prima facie evidence of an increase in sample size, as well as a smaller standard deviation of the distribution of social security benefits. However, the fact that we use replacement rates, not the level of pension benefits, makes it difficult to compare their findings to ours. The ultimate test would be to use both the probabilistic format and an alternative way of eliciting expectations (such as the visual format of Delavande and Rohwedder (2008)). For the probabilistic format, respondents should be forced to provide consistent answers, but the information on inconsistent responses should be stored. Only then can we make a comparison between the various formats, as well as give a judgement on the informative value of the subjective expectations.

As an application, one can use the expected pension income and pension risk based on the (computed) replacement rates and, for instance, estimate a life–cycle model of consumption without the need to arbitrarily assume how expectations are formed. An important implication of our findings for such research is that one must account for the endogenous selection effects due to incorrect responses. An interesting extension of our study is to examine how persistent expectations are. That is, we have shown some dispersion in the expected replacement rate in a (pooled) cross–section, but to obtain further insights in expectation formation, it would be of interest to analyze at the individual level how expectations are updated when new information becomes available. Hence, the persistency of these expectations can tell us something about how expectations are formed. Such an extension may require a longer panel than we currently have and is left for future research.

Chapter 3

Uncertain pension income and household saving*

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* This chapter is based on Van Santen (2012).

3.1 Introduction

The standard lifecycle model emphasizes the importance of saving during working life for consumption during retirement. A simple version of this model predicts that private savings decreases one-for-one with increases in pension wealth, that is, perfect displacement (or crowding out) of private savings by pension savings. The displacement effect is an important policy parameter to assess the welfare effects of changes in the pension system. In particular, less than perfect displacement would suggest that households save too little to smooth consumption over the lifecycle. This notion ignores precautionary saving motives to compensate possible adverse labor market outcomes or lower than expected retirement income. The aim of this paper is to allow for a precautionary saving motive stemming from uncertainty in pension benefits, and to estimate both the displacement effect as well as the precautionary effect using micro data.

I use data from the DNB Household Survey (DHS), an annual survey collecting panel data from the Netherlands on household income, wealth and demographics, and the Pension Barometer, an annual survey presented to a subset of respondents from the DHS, which elicits expectations of pension benefits. To be precise, the expectations of pension benefits are elicited from probabilistic survey questions of the type suggested by Dominitz and Manski (1997) and Manski (2004). These questions allow for the calculation of the expected level of the retirement income replacement rate, as well as the standard deviation of the replacement rate. I have subjective expectations data at my disposal for the period 2006-2011, and both the expected level of the replacement rate and its variance vary over time and over individuals.

Using quantile regressions, I find no significant displacement effect or precautionary saving effect for the lowest quantiles up to the median. In contrast, for the 75^{th} quantile of the saving rate distribution, I find that the saving rate increases by 0.69 percentage points for every decrease in the individual-specific expected retirement income replacement rate by 1 percentage point. An increase of 1%-point in the individual-specific standard deviation of the replacement rate, as a measure of uncertainty, increases the saving rate by 0.37 %-point. For the 90^{th} quantile, the saving rate increases by 1.27%-point and 0.96%-point for the same decrease in the expected replacement rate and increase in its standard deviation. In level terms, a back-of-the-envelope calculation implies that for every extra Euro in expected pension wealth, private wealth decreases by 11.5 cents, or a displacement effect of 11.5%, for the 75th quantile, and 21.2% for the 90th quantile. The results match up with the estimate of Kapteyn et al. (2005), who exploit productivity differences across cohorts and the introduction of social security in the Netherlands to find a small but statistically significant displacement effect of 11.5%. Moreover, the finding of insignificant displacement in the lowest part of the saving rate distribution is consistent with a lifecycle consumption model with a liquidity constraint, presented in Section 3.3, as well as the empirical evidence in Jappelli (1995) and Engelhardt and Kumar (2011).

The main contribution is in allowing for the precautionary saving motive.[1] The results show that, in the highest quantiles, saving increases with uncertainty. For the lower quantiles, I find no evidence of precautionary saving, which is again consistent with the lifecycle model with liquidity constraints. Previous empirical literature has not accounted for the precautionary motive. The resulting omitted variable bias is likely to produce a too large estimate of (the absolute value of) the crowding out of private saving by pension wealth, as long as the true precautionary saving parameter is positive. Indeed, for the 75th quantile, I find that ignoring the uncertainty in pension benefits yields a increase in the saving rate of .8%-point for a 1%-point decrease in the expected replacement rate. For the 90th quantile, the saving rate increases by 1.5%-point. For the median respondent, I find a significant displacement effect (0.5%-point) when ignoring uncertainty, but an insignificant effect when accounting for uncertainty. Obviously, this casts doubt on the estimates obtained in previous studies. In the lowest part of the distribution, the bias in previous studies may not be too large.

Since the seminal article of Feldstein (1974), many studies have made attempts to estimate the displacement effect. Gale (1998) estimates the displacement effect of pensions on non-pension wealth to be 82.3% (39.3%) using median (robust) regressions. Engelhardt and Kumar (2011) and Alessie et al. (2011a) use data on the

[1] The theoretical work of Skinner (1988), Zeldes (1989) and Caballero (1990,9) emphasize the importance of precautionary savings in aggregate savings. Empirical evidence of precautionary saving behavior is also found in, among others, Lusardi (1998), Guariglia (2001) and Brown and Taylor (2006).

earnings history of older respondents from, respectively, the Health and Retirement Study in the US and the SHARE household survey in Europe. Both studies estimate a model for discretionary household wealth as a function of pension wealth, and find evidence of limited displacement, between 47% and 67%. Attanasio and Rohwedder (2003) and Attanasio and Brugiavini (2003) estimate a model for annual household saving, using pension reforms in the United Kingdom and Italy respectively to offset endogeneity and attenuation biases affecting the displacement effect. Attanasio and Brugiavini (2003) find that the displacement effect differs per age group, ranging from close to zero for young adults and nearly retired individuals to 200% for middle-aged individuals, although the coefficients differ per specification. Attanasio and Rohwedder (2003) find that the displacement effect is close to zero for the basic state pension, and ranges from 55% for middle aged to 75% for nearly retired individuals regarding occupational pensions.

The regression equations in the papers above are based on either certainty or certainty equivalence. Moreover, expectations are taken to be rational and static, meaning that the introduction of the social security system in Kapteyn et al. (2005) or the reform of the pension system in Attanasio and Rohwedder (2003) or Attanasio and Brugiavini (2003) comes as a surprise, that households perfectly understand the consequences of the change in the pension system and that the change is considered to be permanent and, therefore, immediately incorporated into household consumption and saving programs over the lifecycle. Instead, I have available expectations of the pension income replacement rate for several time periods in a panel of households. I do not have to make restrictive assumptions on the expectation formation process, nor assume static expectations. A few other studies have also relaxed the assumption on static expectations by using subjective expectations data. Guiso et al. (1992) analyze precautionary saving against uncertain labor earnings, while Guiso et al. (1996) analyze portfolio choice in the presence of income risk. Bottazzi et al. (2006) use a subjective measure of expected pension benefits to study displacement of private wealth by social security wealth; their IV estimate of the displacement effect equals 64.5% using Italian pension reforms to identify this effect. Guiso et al. (ming) use similar probabilistic survey questions as used in this paper to calculate individual-level expected replacement rates of pension income, as well as the standard deviation as measure of uncertainty. Using probit regressions on a cross-section of Italian investors, the authors find that the probability of investing in a pension fund decreases with the expected replacement rate, and increases with its standard deviation, in line with the lifecycle model. The same sign and significance are obtained for the probability of having health insurance. This paper extends the analysis of Guiso et al. (ming) by using a saving equation derived from a lifecycle model.

The paper is organized as follows. Section 3.2 briefly discusses the Dutch pension system. Section 3.3 presents the theoretical model, with derivations delegated to the appendix. Section 3.4 discusses the data and Section 3.5 presents the results. Section 3.6 concludes.

3.2 Uncertainties in the Dutch pension system

The Dutch pension system consists of three pillars.[2] The first pillar is the flat-rate state pension benefit, provided to all inhabitants aged 65 and above. In 2010, the gross monthly benefit amounted to €1057 for singles and €1470 for couples. The second pillar, the occupational pensions, are mandatory for most employees, and both employers and employees contribute to a (usually defined benefit) pension fund. Traditionally, the Dutch occupational pension system is one of the most developed in the world, with pension funds holding around 125% of Dutch GDP in investments in 2008. Finally, the third pillar concerns private pension savings, such as annuities bought from banks or insurance companies or private retirement saving accounts. The third pillar is less popular in the Netherlands, as documented by Mastrogiacomo and Alessie (2011). This paper concerns pension benefit expectations from the first and second pillars together.

Bodie (1990) argues that employer pensions can serve as insurance against replacement rate inadequacy, deterioration of social security benefits, longevity risk, investment risk and inflation risk. However, this "insurance contract" is far from complete. The recent turmoil on financial markets after the subprime mortgage crisis in the US, followed by a global financial, economic and debt crisis, and the ag-

[2] See Bovenberg and Gradus (2008) for an overview of the Dutch pension system and its reforms.

ing of the population in many developed economies has led to revisions in pension systems worldwide. In the Netherlands, these include an increase in the statutory retirement age, from currently 65 to 67 in 2023. Furthermore, the occupational pension system will shift from a defined benefit (DB) to a defined contribution (DC) system, making explicit the dependence of pension benefits on asset returns. Since 2009, Dutch pension funds have taken different measures during the crisis due to underfunding resulting from sharp negative investment returns, including a reduction of nominal accrued pension rights, increasing the pension premium and/or not adjusting pension wealth to inflation. Hence, already under the implicitly risky DB contracts and after the transition to the DC system, income after retirement is not as certain as usually perceived.

Since the sample period (2006-2011) includes this period of turbulence, it is important that the expectations from the survey questions I use in this paper do reflect this. I have reason to believe that this is indeed the case. First, Van Santen et al. (2012) reports that the (average) expected replacement rate, calculated from the same data as used in this study, has been decreasing over time (see also Section 3.4). Likewise, the (average) variance of the replacement rate has increased over time. Second, Van der Wiel (2009) studies the effect of public debate on the expectations of the statutory retirement age in the Netherlands, using data from the monthly version of the Pension Barometer. The author finds a large effect of publicity on expectations for less-educated individuals and for those that stated not to read the newspapers.

3.3 Model

The theory on income uncertainty presented here is not new in any respect. The model is in the spirit of the two-period consumption model of Leland (1968), who analyzes precautionary saving if second-period (pension) income is unknown, but the individual does have a subjective distribution of future (retirement) income in mind when taking decisions; Leland (1968) shows saving is increasing in uncertainty. I consider a finite horizon discrete-time lifecycle model with uncertainty over both pension income and length of life. I assume a certain level of labour income, a certain interest rate and an exogenous date of retirement. The current period is denoted by period t. The individual's[3] remaining lifetime is divided into two parts, the working stage and the retirement stage. I make the following assumptions:

- The per-period utility function is of the Constant Absolute Risk Aversion (CARA) type[4] , $U(c) = -(1/\alpha)\exp(-\alpha c)$ with coefficient of absolute risk aversion α.
- Retirement is exogenous, and occurs at age K.
- Income during working life, y_τ is certain and exogenous but varies with age τ.
- Retirement income, y_K, is a normally distributed[5] random variable with mean μ_{y_K} and variance $\sigma^2_{y_K}$. Income after retirement is constant.
- Survival is guaranteed until retirement; after retirement the survival probability up to period $\tau > K$ is denoted a_τ. The maximum attainable age is denoted by L.
- The interest rate, r is constant and equal to the rate of time preference, ρ. For notational convenience, I define $R = 1 + r$ and $\beta = (1+\rho)^{-1}$ as interest factor and discount factor, respectively.

The problem the currently young individual faces is to maximize lifecycle utility subject to the consolidated lifetime budget constraint. Formally, the problem reads

$$\max_{c_\tau} -\frac{1}{\alpha}\sum_{\tau=t}^{K-1}\beta^{\tau-t}\exp\left[-\alpha c_\tau\right] - \frac{1}{\alpha}E_t\sum_{\tau=K}^{L}\beta^{\tau-t}a_\tau\exp\left[-\alpha c_\tau\right] \tag{3.1a}$$

$$\text{s.t.} \sum_{\tau=t}^{K-1}R^{t-\tau}c_\tau + \sum_{\tau=K}^{L}R^{t-\tau}c_\tau = RA_{t-1} + \sum_{\tau=t}^{K-1}R^{t-\tau}y_\tau + \sum_{\tau=K}^{L}R^{t-\tau}y_K\,, \tag{3.1b}$$

[3] I abstract from intra-household decision making, and hence write "the individual" to mean the collective household. In the empirical application, I use data from the head of the household for estimating the model.

[4] The choice of a CARA utility function is motivated by the possibility to obtain closed-form solutions, which is not possible with the class of Constant Relative Risk Aversion (CRRA) utility functions. This choice prevents buffer-stock saving behavior (Carroll, 1992), which needs decreasing absolute risk aversion. See also Blau (2011), who studies displacement in a rich, uncertain environment with CRRA utility.

[5] Lam (1987) discusses more general distributions for income under CARA utility. Normality is not imposed in the empirical application.

where c_τ is consumption in period τ, A_{t-1} is predetermined wealth and E_t is the expectation operator conditional on information available in period t. I solve for today's consumption, c_t, in three steps. First, I solve the retirement stage and calculate the value of future utility streams, conditional on wealth available at the beginning of retirement, A_{K-1}. Second, I solve the problem for the working stage, and compute the value of utility conditional on leaving A_{K-1} available for future consumption. Finally, I choose A_{K-1} to maximize lifecycle utility. Appendix 3.A shows the complete derivation of the model. Current consumption is given by

$$c_t = \frac{RA_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau + \sum_{\tau=K}^{L} R^{t-\tau} \mu_{y_K}}{\sum_{\tau=t}^{L} R^{t-\tau}} - \frac{\sum_{\tau=K}^{L} R^{t-\tau} \left(\frac{1}{\alpha} \log\left(a_\tau\right) + \frac{1}{2} \alpha \sigma_{y_K}^2 \right)}{\sum_{\tau=t}^{L} R^{t-\tau}} . \tag{3.2}$$

This is the closed-form expression for today's consumption when future pension income is uncertain. The first term is the familiar expected present value of future income streams (or permanent income). Without uncertainty, consumption would be equal to permanent income. With uncertainty, consumption equals permanent income minus precautionary saving due to lifetime and pension income uncertainty. If the probability of survival increases ($a_\tau \uparrow$), consumption decreases, a result that is also found under the well-documented 'certainty equivalence' case.[6]

The most interesting feature of the solution is the explicit relationship between consumption and the variance in pension benefits, which is absent in the certainty equivalence case. Uncertainty in pension income induces consumers to spend less, and hence to save more. The consumption function I obtain is similar to the consumption function found in Caballero(1990,1991). Cantor (1985) has shown the same solution for current consumption when income is normally distributed but neglecting lifespan uncertainty.

The DHS dataset does not obtain information on consumption or expenditures, but I do have data on annual saving. The closed-form solution for current saving,

[6] For the certainty equivalence case, where $U(c_\tau) = -\frac{1}{2}\left(\bar{c} - c_\tau\right)^2$, current consumption would be equal to $c_t = \frac{RA_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau + \sum_{\tau=K}^{L} R^{t-\tau} \mu_{y_K} + \bar{c} \sum_{\tau=K}^{L} (1-a_\tau) \frac{R^{t-\tau}}{a_\tau}}{\sum_{\tau=t}^{K-1} R^{t-\tau} + \sum_{\tau=K}^{L} \frac{R^{t-\tau}}{a_\tau}}$, with $\frac{\partial c_t}{\partial a_\tau} < 0$.

$s_t = (R-1)\,A_{t-1} + y_t - c_t$ can be written as

$$s_t = -\frac{R^{t-L}}{\sum_{\tau=t}^{L} R^{t-\tau}} A_{t-1} + \frac{\sum_{\tau=K}^{L} R^{t-\tau} y_t}{\sum_{\tau=t}^{L} R^{t-\tau}} - \frac{\sum_{\tau=K}^{L} R^{t-\tau} \mu_{y_K}}{\sum_{\tau=t}^{L} R^{t-\tau}}$$
$$- \frac{\sum_{\tau=t+1}^{K-1} \Delta y_\tau \sum_{q=\tau}^{K-1} R^{t-q}}{\sum_{\tau=t}^{L} R^{t-\tau}} + \frac{\sum_{\tau=K}^{L} R^{t-\tau} \frac{1}{\alpha} \log\left(a_\tau\right)}{\sum_{\tau=t}^{L} R^{t-\tau}} + \frac{\sum_{\tau=K}^{L} R^{t-\tau} \frac{1}{2} \alpha \sigma_{y_K}^2}{\sum_{\tau=t}^{L} R^{t-\tau}}\,, \tag{3.3}$$

where Δ is the backward difference operator. Previously accumulated assets have a negative impact on saving, and if labor income increases with age ($\Delta y_\tau > 0$), today's saving will also be lower. Higher expected pension benefits should decrease saving, i.e. the displacement effect referred to in Section 3.1 is present here as well. Uncertainty in pension income increases saving, i.e. a precautionary saving motive, as does longer expected survival.

3.3.1 Model extensions

Although equation 3.3 is the equation to be estimated in Section 3.5, I consider deviations from the assumptions implicitly or explicitly made so far. There are many deviations possible, such as[7] stochastic labor income (Caballero, 1990) or interest rates (Merton, 1973), endogenous labor supply and retirement (Feldstein, 1974), hyperbolic discounting (Laibson, 1998), habit formation (Angelini, 2009; Alessie and Teppa, 2010), home production (Aguiar and Hurst, 2005, 2007), bequest motives (Hurd, 1989) or liquidity constraints (Mariger, 1987; Deaton, 1991), all of which will have an impact on current consumption. Here I consider liquidity constraints explicitly in the model presented above to guide the empirical approach. This choice is partly based on the notion that negative consumption, which is not punished much under CARA utility as opposed to CRRA utility, is ruled out explicitly, and partly based on the finding in Gross and Souleles (2002) that precautionary motives, liquidity constraints and a combination of these are empirically important for consumption behavior.

I use the approach of Mariger (1987) to incorporate a liquidity constraint, which consists of the following steps:

1. Let today be denoted by time t, and assume $A_{t-1} > 0$. Assume that there

[7] This list of possible deviations is certainly not exhaustive, as is the list of references given here. See Attanasio and Weber (2010) for a recent review.

exists a date v in the future, such that the liquidity constraint binds at this date for the first time, A_v=0. Afterwards, the constraint always binds.

2. Solve the unconstrained problem for periods t until v

3. The (endogenous) date v can be found by choosing the maximum date that minimizes period t consumption.

See Mariger (1987) for details and a proof. The derivations are delegated to Appendix 3.B; here I focus on the intuition. There are four scenarios possible. First, the liquidity constrained may be currently binding ($v = t$). Under the maintained assumption that the liquidity constraint always binds after reaching the zero-assets bound for the first time, today's consumption will be equal to today's income, and saving is zero, independent of retirement income. Second, the constraint may never bind ($v = L$), and we are back with the unconstrained solution presented above. Third, the constraint may become binding before retirement ($t < v < K - 1$). In this scenario, today's consumption equals the present value of income until the binding date. The individual's horizon is shortened to a period before retirement, and hence his consumption decision is independent of income after retirement. In this case, there should be no displacement effect nor a precautionary saving effect; saving is independent of the expected level of pension income, μ_{y_K} and independent of the variance of pension income, $\sigma^2_{y_K}$. In the final scenario, the liquidity constraints binds after retirement ($K < v < L$). In this case, there exists an interplay between the survival curve and the binding date. Consumption and saving are functions of μ_{y_K} and $\sigma^2_{y_K}$, but the marginal effects depend on the exact binding date.

In general, the level of pension income as well as the uncertainty in pension income will exhibit a larger influence on current consumption, the later in life the liquidity constraint binds. Moreover, the higher are predetermined assets and labor income, the later in life the liquidity constraint will bind.[8] In the empirical section, these observations are explicitly taken into account, by making the marginal effect of pensions on saving dependent on predetermined assets and labor income, using quantile regressions; more details follow in Section 3.4.1.

[8] This prediction of the model is consistent with the notion that liquidity constraints are likely to impact especially young households (Meghir and Weber, 1996), who have low levels of wealth and a steep age-earnings profile.

3.4 Data and methodology

For the empirical analysis, I use two sources of survey data: the DNB Household Survey (DHS) and the Pension Barometer (PB). Both surveys are administered by CentERData, Tilburg, The Netherlands, and have unique identifiers allowing us to merge the two data sets at the individual level. The respondents represent the Dutch population aged 16 and above. Both surveys are administered via the internet, and internet access is provided to those that do not have access themselves. The DHS has been running since 1993, and the data from 2011 are the most recent available. The DHS collects information on many socio-economic characteristics of the household, including a detailed breakdown of household income and wealth holdings, which can be used to construct measures of total assets, financial assets and housing assets; see Alessie et al. (2002) for an extended description.

The Pension Barometer survey is administered to a subset of respondents from the DHS. The survey started in 2006, and 2011 is the most recent survey year at my disposal. Among other questions, the PB elicits expectations of pension benefits from employees aged below the statutory retirement age of 65. More specifically, the PB contains probabilistic survey questions of the type suggested by Dominitz and Manski (1997) and Manski (2004) that elicit the subjective distribution of the pension income replacement rate. Using the responses to these questions allows us to construct individual-specific measures of expected pension benefits and subjective uncertainty of pension income, by calculating the first and second moment of the distribution.

The exact wording of these questions is as follows.

Question 3.1. *At which age do you think you can retire at the earliest, following your employer's pension scheme?*

The answer to this question, say age K, is used in the subsequent question:

Question 3.2. *If you would retire at age K, please think about your total net pension income including social security, compared to your current total net wage or salary. What do you think is the probability that the purchasing power of your total net pension income in the year following your retirement will be:*

a)	*more than 100% of your current net wage?*	... %
b)	*less than 100% of your current net wage?*	... %
c)	*less than 90% of your current net wage?*	... %
d)	*less than 80% of your current net wage?*	... %
e)	*less than 70% of your current net wage?*	... %
f)	*less than 60% of your current net wage?*	... %
g)	*less than 50% of your current net wage?*	... %

The probabilities answered by the respondent define 7 points on the subjective cumulative distribution function of pension income. I assume a maximum replacement rate of 120%, and use linear interpolation between the thresholds to derive the complete distribution for each respondent in each survey year. The expected replacement rate, i.e. the first moment, is then used as a measure of the expected level of pension benefits divided by current income, μ_{y_K}/y_t. The standard deviation, that is, the square root of the second central moment, is used as the measure of replacement rate uncertainty, σ_{y_K}/y_t.[9] The determinants of the expected value and standard deviation of the replacement rate have been investigated in Van Santen et al. (2012), who show that the expected benefit is U-shaped in age with a minimum at 48, while uncertainty is inverted U-shaped with age with maximum at age 36. Educational attainment depresses the expectation, and increases uncertainty. The uncertainty was higher in 2008 and 2009, compared to 2006 and 2007, possibly due to the financial crisis. Similarly, the expected replacement rate was lower in these years.

Moreover, Van Santen et al. (2012) show that the sample from which consistent answers are obtained, i.e. probabilities in line with the law of total probability and monotonicity of the cumulative distribution function, is a selected sample. For this reason, I construct sampling weights to correct for selection bias, detailed in Section 3.4.2 below.

Lifespan is the second source of uncertainty in the model. For the empirical specification, I rely on questions from the DHS which ask respondents to provide subjective survival probabilities for certain target ages:

Question 3.3. *How likely is it that you will attain (at least) the age of* 65 / 75 / 80 ?[10]

[9] Results using the inter-quartile range are very similar; the correlation between the IQR and the standard deviation is 0.90.

[10] Respondents answer at most three, but mostly two questions, depending on their actual age. Respondents younger than 55 provide survival probabilities up to age 65 and 75, while people aged 55-65 provide survival probabilities for age 75 and 80. This ensures that respondents do not have to answer survival probabilities up to ages lower than their actual age nor ages in the near (5 years) future.

Please indicate your answer on a scale of 0 thru 10, where 0 means 'no chance at all' and 10 means 'absolutely certain'.

I fit a two-parameter Gompertz distribution to the answers to estimate the subjective survival curve for each respondent in each year, in line with the theoretical model. The cumulative Gompertz distribution function reads (Willemse and Koppelaar, 2000)

$$F(q) = P(T \leq q) = 1 - \exp\left[\exp\left[-\frac{\lambda}{b}\right] - \exp\left[\frac{q-\lambda}{b}\right]\right], \tag{3.4}$$

where T is the time of death and q is the target age. I estimate the parameters b and λ using a nonlinear least squares procedure, separately for each respondent in each year. Furthermore, I use a discrete approximation to the continuous distribution to compute remaining life expectancy as

$$\begin{aligned} E\left(T|T \geq t\right) \approx \sum_{\tau=t}^{\infty} \tau\left[P(T \geq \tau|T \geq t) - P(T \geq \tau+1|T \geq t)\right] = \\ \sum_{\tau=t}^{\infty} P(T \geq \tau|T \geq t) = \sum_{\tau=t}^{\infty} \frac{\exp\left[-\exp\left[\frac{\tau-\lambda}{b}\right]\right]}{\exp\left[-\exp\left[\frac{t-\lambda}{b}\right]\right]}. \end{aligned} \tag{3.5}$$

The expected age of death then equals $\widetilde{L} = E\left(T|T \geq t\right) + t$. This measure is used in the descriptive analysis only,[11] as the maximum attainable age of the model, L, is fixed at 110 in the empirical work.

The dependent variable, annual saving, is computed as the change of financial wealth, $s_t = A_t - A_{t-1}$, and financial wealth equals the sum of the most liquid assets (checking accounts, saving arrangements, deposit books, saving or deposit accounts, saving certificates) net of the most liquid categories of liabilities (private loans and extended lines of credit). Note that this saving measure is backward looking: saving in year t is the change of financial wealth between years $t-1$ and t. On the contrary, the subjective expectations are forward looking: the expected replacement rate obtained in survey year t measures $E_t(y_K/y_t)$, and similarly for the standard deviation of the replacement rate and subjective survival probabilities. In order to relate these expectations to the period in which the saving decision is taken, I use the lagged value of all expectations. Now, there are six observation for financial wealth (2006-2011), and hence five years of saving, related to five years of

[11] Alternatively, the median remaining length of life, $T^{50} = b \log\left(\log(2)\exp\left[b^{-1}(\lambda - t)\right] + 1\right)$, could have been used in the descriptive analysis, which does not require the approximation, but the two are very similar in the data.

expectations data.

The DHS gives additional information on household characteristics, most notably the age of the household members, the size of the household and household income. Table 3.1 below shows the sample statistics of the variables used in this study. All variables refer to the head of household.

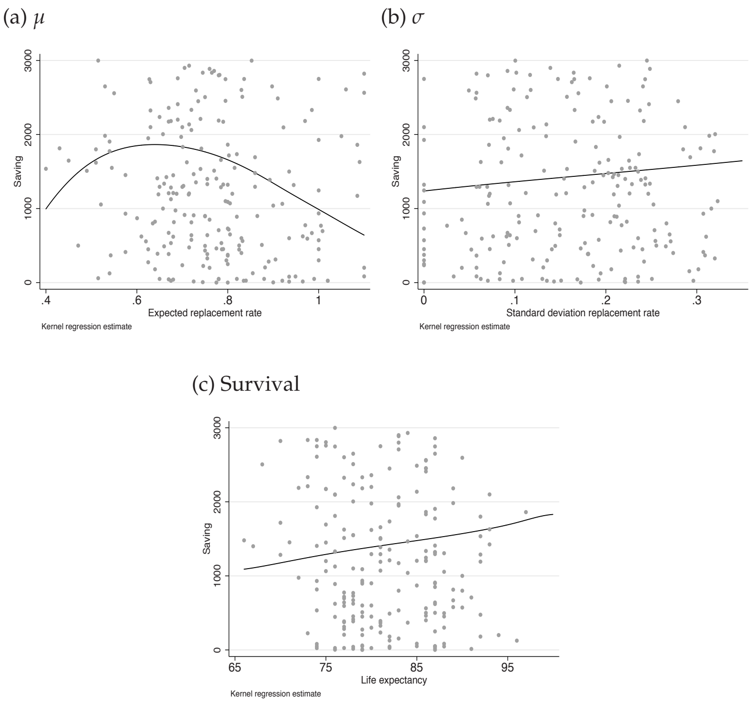
Table 3.1. Summary statistics

Variable		Mean	Standard deviation
	10^{th} Quantile	-9874	
	25^{th} Quantile	-1705	
Saving (s)	50^{th} Quantile	354	
	75^{th} Quantile	6020	
	90^{th} Quantile	22624	
Expected retirement age (K)		63.4	(1.9)
Expected replacement rate (μ_{y_K}/y_t) (%)		75.2	(16.8)
Standard deviation replacement rate (σ_{y_K}/y_t) (%)		15.5	(9.7)
Life expectancy ($\widetilde{L}$)		82.0	8.2
Age (t)		47.3	(9.2)
Real income (y)		35325	(18302)
Financial wealth (A)		44455	(70215)
Low educated (%)		21.4	(41.1)
High educated (%)		50.8	(50.0)
Female (%)		18.4	(38.7)
Partner (%)		69.9	(45.9)
Number of children (%)		1.04	(1.07)
Urban (%)		46.0	(49.9)
Home owner (%)		78.3	(41.2)
Saver (%)		33.6	(47.3)
Bad health (%)		1.7	(13.0)

$N = 1010$. Symbol in parentheses refers to the model of Section 3.3.
Pooled sample statistics for years 2006-2011.

Figure 3.1 plots (bivariate) kernel regression estimates of the relationship hypothesized in the lifecycle model of Section 3.3. As predicted by this model, I observe positive relationships between saving and the uncertainty in pension income (Figure 3.1b) as well as between life expectancy and saving (Figure 3.1c). The relation between saving and the expectation of the replacement rate (Figure 3.1a) appears hump-shaped, although the upward sloping part has few observations; the negative relationship for higher values of the replacement rate is in line with the lifecycle model. Of course, this is just descriptive evidence, and the validity of the model is formally tested in Section 3.5.

Figure 3.1. Kernel regression estimates



3.4.1 Estimation strategy

Since I have panel data I use t to index the age of the head of the household; obviously, t can also be read as the index for year. Households are indexed by i. Annual saving of household i at age t_i, as given by equation 3.3, writing out the summations where possible, equal

$$
\begin{aligned}
s_{it} = & -\frac{(R-1)\,R^{t_i-L}}{R-R^{t_i-L}}A_{it-1} + \frac{R^{t_i-K_{it-1}+1}-R^{t_i-L}}{R-R^{t_i-L}}y_{it} - \frac{\sum_{\tau=t_i+1}^{K_{it-1}-1}\Delta y_{i\tau}\left(R^{t_i-\tau+1}-R^{t_i-K_{it-1}+1}\right)}{R-R^{t_i-L}} \\
& - \frac{R^{t_i-K_{it-1}+1}-R^{t_i-L}}{R-R^{t_i-L}}\mu_{it-1} + \frac{R^{t_i-K_{it-1}+1}-R^{t_i-L}}{2\left(R-R^{t_i-L}\right)}\alpha\sigma_{it-1}^2
\end{aligned}
$$

$$+\frac{(R-1)\sum_{\tau=K_{it-1}}^{L} R^{t_i-\tau}\frac{1}{\alpha}\log\left(a_{it-1\tau}\right)}{R-R^{t_i-L}}+u_{it}\ . \tag{3.6}$$

Note that all variables (except for future income terms in $\Delta y_{i\tau}$) in equation 3.6 are known from the survey questions described above or background characteristics. In particular, t_i is the age of the head of the household, K_{it-1} is the (possibly time-varying) lagged retirement age from question 3.1, A_{it-1} is previous-period liquid wealth, μ_{it-1} is the lagged elicited expected replacement rate multiplied by current income y_{it} and σ^2_{it-1} the variance of the replacement rate multiplied by income squared. $a_{it-1\tau}$ is the lagged subjective survival probability up to age τ, and L the maximum age, which is fixed at 110. All amounts are measured in 2006 Euro's, deflated using the Consumer Price Index from the Statistics Netherlands. The coefficient of risk aversion, α, is not available at the household level; I use $\alpha = 5$ for computing the terms, although the value is not important in the regression analysis as these constants enter linearly. For R, I use $R = 1.03$ as the baseline value, in line with earlier studies (Attanasio and Brugiavini, 2003; Hurd et al., 2012). Robustness checks are performed by varying R between 1.01 and 1.05, and for α between 3 and 7. As for the third term on the right hand side, I use a fixed effects model to predict future labor income, detailed in Appendix 3.C.

One problem with the current specification of the saving equation is that the present value of expected pension benefit receipts and the present value of uncertainty in pension benefits are highly correlated with current income, by construction. Therefore, I divide all terms by $\frac{R^{t_i-K_{it-1}+1}-R^{t_i-L}}{R-R^{t_i-L}}y_{it}$. This transformation implies I can use the expected replacement rate and the standard deviation of the replacement rate as explanatory variables. Note that if I would take the variance of the replacement rate, I would have the saving rate, s/y on the left hand side, and $\sigma^2 \times y$ on the right hand side. If income y is measured with error, which is typically the case in a household survey, the impact of this error is unclear a priori and could bias the results substantially.[12]

In line with the results from the lifecycle model with a liquidity constraint, I let the marginal effect of pension income depend on wealth and labor income. I

[12] Measurement error in the expectation variables, for instance due to the piece-wise linearity assumption made to compute these from the underlying survey questions, is likely to attenuate the coefficients towards zero, and therefore (the absolute value of) these parameters may be underestimated.

impose restrictions on the coefficients for two variables, namely the first term on the right-hand-side, featuring predetermined assets A_{it-1}, and the third term, featuring $\Delta y_{i\tau}$. Both these coefficients are restricted to equal -1, and I subsequently take these variables to the left-hand-side. Of course this also takes care of potential biases from measurement error in household financial wealth and the estimate of future labor income; see Alessie et al. (2011a), for a formal justification of these parameter restrictions.

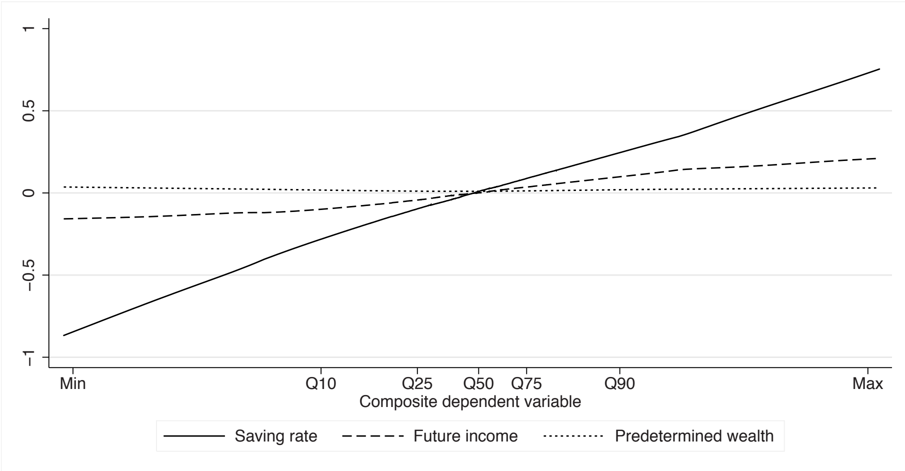
In the empirical application, I additionally control for observable household characteristics, $\boldsymbol{x}_{it}$, such as education and home ownership, and time fixed effects. The final equation to be estimated reads

$$\frac{\left(R - R^{t_i - L}\right) \frac{s_{it}}{y_{it}}}{R^{t_i - K_{it-1}+1} - R^{t_i - L}} + \frac{\left(R-1\right) R^{t_i - L}}{R^{t_i - K_{it-1}-1} - R^{t_i - L}} \frac{A_{it-1}}{y_{it}} + \frac{\sum_{\tau=t_i+1}^{K_{it-1}-1} \frac{\Delta y_{i\tau}}{y_{it}} \left(R^{t_i-\tau+1} - R^{t_i - K_{it-1}+1}\right)}{R^{t_i - K_{it-1}-1} - R^{t_i - L}}$$
$$= \beta_\mu \frac{\mu_{it-1}}{y_{it}} + \beta_\sigma \frac{\alpha \sigma_{it-1}}{2 y_{it}} + \beta_{Survival} \frac{\left(R-1\right) \sum_{\tau=K_{it-1}}^{L} R^{t_i - \tau} \frac{1}{\alpha} \log\left(a_{it-1\tau}\right)}{\left(R^{t_i - K_{it-1}+1} - R^{t_i - L}\right)} + \boldsymbol{x}_{it}' \gamma + u_{it} \tag{3.7a}$$

$$\frac{s_{it}}{y_{it}}^{*} = \beta_\mu \frac{\mu_{it-1}}{y_{it}} + \beta_\sigma \frac{\alpha \sigma_{it-1}}{2 y_{it}} + \beta_{Survival} \frac{\left(R-1\right) \sum_{\tau=K_{it-1}}^{L} R^{t_i - \tau} \frac{1}{\alpha} \log\left(a_{it-1\tau}\right)}{\left(R^{t_i - K_{it-1}+1} - R^{t_i - L}\right)} + \boldsymbol{x}_{it}' \gamma + u_{it} \,, \tag{3.7b}$$

where $\frac{s_{it}}{y_{it}}^{*}$ is the implicitly defined composite dependent variable. I estimate equation 3.7b using quantile regressions (Koenker and Bassett Jr., 1978). The coefficients are now varying over the quantiles of the dependent variable. Of course, quantile regressions have the additional robustness advantage to outliers, compared to linear regression as well. Since I use a composite dependent variable, the interpretation of the coefficients depends on the contribution of each term on the left-hand-side of (3.7a) to the composite variable. Figure 3.2 shows the distribution of the saving rate, the wealth-to-income ratio and the growth rate of labor income, plotted against the distribution of the composite dependent variable. The main source of variation in the composite dependent variable comes from the saving rate. Instead, the wealth-to-income ratio is rather flat. The results are mainly driven by the saving rate. As a check, I have also estimated linear (panel data) models without imposing the restrictions, the results of which are shown in Section 3.5.3.

Figure 3.2. Composition of the dependent variable



3.4.2 Sample selection

The estimation sample is small ($N = 1010$), both in absolute terms and relative to the full dataset if the panel were completely balanced ($N = 2148$). One of the reasons for the small sample size is the fact that, to estimate equation 3.7, one needs at least two time periods to compute the change in financial wealth. Moreover, as the Pension Barometer is a separate questionnaire, that is, not integrated into the DHS, the household head has to answer three questionnaires to be included in the estimation sample: the DHS in years $t-1$ and t, and the PB in $t-1$. The DHS has quite substantial attrition, which is dealt with by biannual refreshment samples that are drawn in view of keeping the panel representative of the Dutch population of 16 years and older. Still, for this analysis, a considerable fraction of the potential sample is lost.

A second major reason for the loss of observations is the fact that many respondents do not answer the probabilistic survey questions in a meaningful way, that is, either no answer or answers violating the law of total probability or violating monotonicity of the distribution function. For these observations, the expected level and standard deviation of the pension income replacement rate cannot be computed. Not surprisingly, education is related to being able to answer the probabilistic questions or not. Van Santen et al. (2012) provide a more thorough discussion of these selection effects. Combining the missing answers due to attrition, item non-response and violations, we lose 1137 out of 2148 observations which have answered at least one DHS questionnaire. To correct for possible attrition and selection biases, I opt for Inverse Probability Weighted estimation (Wooldridge, 2002, 2007) of the quantile regressions, following Maitra and Vahid (2006). As a brief summary, all variables, both dependent and independent, are weighted by the inverse of the probability of being in the estimation sample, in order to obtain a consistent estimator[13] of the population moment condition to which the quantile regression estimator converges[14]. In practice, these probabilities need to be estimated. I use a logit model to estimate the probabilities, in which the dependent variable $D_{it} = 1$ in case the observation is in the estimation sample, and $D_{it} = 0$ otherwise. As explanatory variables, I use a lagged dependent variable (D_{it-1}) to account for attrition, following Abowd et al. (2001), age and its square, the logarithm of real annual household income and the inverse hyperbolic sine transformation of financial wealth. Furthermore, I use a set of indicators for education (reference group: least educated), working as a civil servant, not having a permanent work contract, owning a house, being female, having a partner or spouse, living in an urban area and being in bad health, as reported subjectively by the respondent in the previous survey year. To account for selection effects from not answering the probabilistic pension income questions, I use three variables suggested in Van Santen et al. (2012). These 'excluding variables' are derived from not answering or violating other probabilistic survey questions regarding (1) next-year inflation expectations, (2) next-year household income expectations and (3) next-year household income growth expectations. All three variables are coded 1 in case of not answering or violating probability laws. Finally, I include a household random effect, and solve the initial conditions problem arising from the inclusion of both the lagged dependent variable and the household random effect, following the approach in Wooldridge (2005), by including an indicator (D_{i2005}) for whether

[13] The assumptions needed to ensure that the weighting works are essentially that the selection process is captured by the weights, and that the weights are exogenous to saving.

[14] Buchinsky (1998) corrects for attrition bias using a Heckman-type correction for quantile regression models.

Table 3.2. Results logit model for probability weights

	Coefficient	Standard error
D_{it-1}	0.775***	(0.152)
D_{i2005}	0.165	(0.242)
Inflation error	-0.387***	(0.150)
Income error	-0.558***	(0.177)
Income growth error	-0.404	(0.359)
Age	0.758***	(0.0982)
$\text{Age}^2/100$	-0.864***	(0.105)
Log real income	0.593***	(0.215)
IH(financial wealth)	-0.0211	(0.0243)
Secondary educated	-0.463*	(0.269)
Higher educated	0.185	(0.276)
University educated	0.560*	(0.339)
Female	-0.0151	(0.268)
Partner	0.214	(0.263)
Log (Nr children+1)	-0.227	(0.220)
Civil Servant	-0.332	(0.256)
No permanent contract	-0.689*	(0.377)
Home owner	0.668***	(0.247)
Urban area	0.206	(0.206)
Bad health	-2.425***	(0.543)
Constant	-4.732*	(2.618)
Observations	2148	
Households	1013	
p-value Model	0.000	
p-value Excluding variables	0.000	
p-value Age effects	0.000	
p-value Income effects	0.000	
S.D. Random effect	1.099	

Dependent variable $D_{it} = 1$ if in estimation sample
Panel-robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

or not the respondent answered the DHS questionnaire in 2005 (period 0).[15] The results are shown in table 3.2 below.

Being a respondent to both the DHS and PB questionnaires in period $t-1$ increases the probability of being in the sample, but at a diminishing rate, confirming the attrition taking place in the sample. As in Van Santen et al. (2012), education and whether the respondent does not answer the other probabilistic questions on next-year inflation and household income (growth) correctly or does not answer at all are good predictors of the selection effects from the probabilistic survey questions on retirement income used in this paper. Older individuals

[15] The results of the quantile regressions discussed in Section 3.5 are marginally affected by the inclusion of the lagged dependent variables D_{it-1} and D_{i2006}, i.e. not considering panel attrition, in the sense that the qualitative conclusions are the same, but the estimated coefficients (and their significance levels) are somewhat smaller in absolute values. The biggest effect is noticeable for the variable σ, which, compared to Table 3.3 is now significant at the 10% level (as opposed to the 5% level) for the highest two quantiles. These results are available upon request.

are less likely to be in the sample, probably due to the fact that the retirees are of course excluded from the analysis. Finally, being in bad health in the previous year decreases the probability of being in the estimation sample. In the quantile regressions below, I use the variables used are $\widetilde{y}_{it} = y_{it}/\widehat{P}(D_{it} = 1)$ and $\widetilde{z}_{it} = z_{it}/\widehat{P}(D_{it} = 1)$ as dependent and independent variables, respectively, where $z_{it} = \left(\mu_{it-1}/y_{it}, \alpha\sigma_{it-1}/2y_{it}, (R-1)\sum_{\tau=K_{it-1}}^{L} R^{t_i-\tau}(1/\alpha)\log\left(a_{it-1\tau}\right) / \left(R^{t_i-K_{it-1}+1} - R^{t_i-L}\right), x'_{it}\right)$.

3.5 Results

Table 3.3 shows the results of estimating equation 3.7b for the 10%, 25%, 50%, 75% and 90% quantiles. I use the abbreviations μ, σ and Survival to refer to the expected replacement rate, standard deviation of the replacement rate distribution and the subjective survival probabilities, respectively. The standard errors are based on a bootstrap procedure. I draw bootstrap samples of households (sampling all years the household is in the data) from the entire dataset (i.e. 2148 observations) to calculate a set of probability weights, and subsequently estimate the weighted quantile regression coefficients. This procedure is repeated 1000 times to obtain cluster-bootstrapped standard errors, taking into account the uncertainty from estimating the inverse probability weights. The control variables consist of the same set as used in Table 3.2, and include the logarithm of the number of children and indicators for education (secondary, more than secondary or university education with benchmark least educated), being female, having a partner or spouse, being a civil servant, not having a permanent contract (benchmark flexible or short-term contracts), owning a house, living in an urban area (benchmark living in villages with population less than 10,000 persons) and being in bad health as reported by the person, as well as time fixed effects. The main results are presented in Table 3.3.

The coefficients measuring the displacement effect (μ) and the precautionary saving effect (σ) are insignificant for the lower part of the saving distribution. For the 75$^{\text{th}}$ and 90$^{\text{th}}$ quantiles, we find significant evidence of displacement, and evidence for precautionary saving behavior. The coefficient estimates for the higher quantiles are in line with the theoretical model. Across the entire distribution, the results are consistent with the liquidity-constrained version of the model, as the

Table 3.3. Results saving equation, weighted quantile regressions

	Quantile (10%)	(25%)	(50%)	(75%)	(90%)
μ	0.452*	-0.0163	-0.0424	-0.693***	-1.273**
	(0.272)	(0.125)	(0.0806)	(0.284)	(0.550)
σ	-0.178	-0.122	-0.00693	0.365**	0.964**
	(0.226)	(0.0977)	(0.0668)	(0.163)	(0.348)
Survival	-2.318***	-0.863***	0.320	1.294***	2.435***
	(0.562)	(0.281)	(0.267)	(0.476)	(0.973)
Secondary educated	-0.309**	-0.252***	-0.0574	-0.206**	-1.052***
	(0.137)	(0.0533)	(0.0366)	(0.0808)	(0.322)
Higher educated	0.527***	0.158***	0.0978***	0.143*	-0.0767
	(0.117)	(0.0525)	(0.0361)	(0.0800)	(0.338)
University educated	0.192	0.242***	0.141***	0.0743	-0.0595
	(0.200)	(0.0712)	(0.0438)	(0.0982)	(0.338)
Female	-1.806***	-0.521***	-0.0762*	-0.200***	0.214
	(0.135)	(0.0573)	(0.0412)	(0.0578)	(0.133)
Partner	-0.532***	-0.510***	0.0390	0.104	1.444***
	(0.121)	(0.0535)	(0.0406)	(0.0792)	(0.167)
Log(Nr children+1)	0.287***	0.147***	-0.128***	-0.244***	-0.800***
	(0.111)	(0.0456)	(0.0287)	(0.0473)	(0.143)
Civil servant	-0.392***	-0.324***	-0.0466	-0.0931*	0.292**
	(0.134)	(0.0558)	(0.0329)	(0.0527)	(0.143)
No permanent contract	0.560	-0.0307	0.201*	0.0991	0.127
	(0.383)	(0.254)	(0.111)	(0.0955)	(0.184)
Home owner	-0.0813	0.0929**	0.0318	0.0526	0.238
	(0.107)	(0.0461)	(0.0368)	(0.0658)	(0.170)
Urban area	0.302***	0.0353	0.0489	0.0223	0.283**
	(0.0936)	(0.0442)	(0.0328)	(0.0516)	(0.138)
Bad health	-0.550	-0.0567	-0.182	-0.206	-2.079***
	(0.406)	(0.453)	(0.228)	(0.151)	(0.301)
Year 2007	0.0699	-0.176***	-0.174***	-0.0273	-0.0243
	(0.154)	(0.0488)	(0.0404)	(0.0564)	(0.137)
Year 2008	-0.549***	-0.355***	-0.151***	-0.0738	-0.184
	(0.131)	(0.0571)	(0.0401)	(0.0644)	(0.158)
Year 2009	-0.439***	-0.293***	0.00831	0.245***	0.0162
	(0.0951)	(0.0503)	(0.0422)	(0.0619)	(0.206)
Year 2010	-0.415*	-0.348**	-0.0535	0.351	1.691
	(0.250)	(0.136)	(0.0646)	(0.302)	(1.794)
Year 2011	-1.583***	-0.334***	-0.150***	-0.0453	-0.0963
	(0.187)	(0.0615)	(0.0413)	(0.105)	(0.403)
Constant	-1.743***	0.149	0.370***	1.098***	3.997***
	(0.354)	(0.166)	(0.109)	(0.190)	(0.536)
Observations	1010	1010	1010	1010	1010
Households	491	491	491	491	491

Cluster-bootstrapped standard errors in parentheses; 1000 replications
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

lower quantiles represent those with less assets and less income. I find that the saving rate increases by 0.69 percentage points for every 1 percentage point decrease in the expected replacement rate. An increase of 1%-point in the standard deviation of the replacement rate increases the saving rate by 0.37 %-point. For the 90th quantile, the saving rate increases by 1.27%-point and 0.96%-point for the same decrease in the expected replacement rate and increase in its standard deviation.

For Survival, I obtain strong negative effects in the lower quantiles, no effect at the median and positive effects at the high quantiles. The theory predicts a positive effect, hence saving to hedge against becoming very old is therefore only true for the wealthiest households in the sample. Female-headed households and civil servants save less, except at the highest quantile.

The results show evidence in favor of the lifecycle model with uncertainty. An interesting test is to see what the impact is of ignoring uncertainty, and hence estimating a certainty-equivalence version of the lifecycle model. To do so, I estimate the same model as in Table 3.3, without σ and Survival as explanatory variables. The result of the parameter governing the displacement effect is shown in Table 3.4 below.

Table 3.4. Results saving equation without uncertainty, weighted quantile regressions

	Quantile				
	(10%)	(25%)	(50%)	(75%)	(90%)
μ	1.044	-0.281	-0.489**	-0.795**	-1.498**
	(0.846)	(0.353)	(0.224)	(0.366)	(0.595)
Observations	1010	1010	1010	1010	1010
Households	491	491	491	491	491

Cluster-bootstrapped standard errors in parentheses; 1000 replications
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Same controls as in Table 3.3

The displacement effect is negative from the 25th quantile, and significantly below zero from the median upwards. This result is interesting, as it shows that ignoring precautionary saving motives leads to underestimation of the displacement effect parameter, and therefore gives too high estimates of crowding out. In a simple omitted variable bias setting, this result can be easily explained as long as the true precautionary saving parameter is positive.[16] Previous studies may therefore have overestimated the crowding out effect even when using linear or median regressions.

The remainder of this section shows the results of two robustness checks, namely accounting for unobserved heterogeneity. More checks have been done however, in particular, 1) varying the fixed parameters r (between 1-5%) and α (between 3 and 7), 2) a broader measure of saving (wealth) based on changes in (the level of) net wealth (which includes housing wealth, mortgage debt and durable goods) as well as 3) an interaction between the civil servant dummy and both μ and σ, to capture labor income uncertainty or differences in risk aversion. For brevity, these are not reported, but available upon request. The results of these checks show that 1) varying r and α gives quantitatively different results (in particular, higher interest rates give larger coefficients in absolute value terms), but leaves the qualitative results unchanged, 2) broader saving and wealth measures give evidence of displacement and precautionary saving only in the highest quantile[17] and 3) income uncertainty seems to play a less prominent role, as the interaction terms are marginally significant only in the highest quantile.

3.5.1 Unobservable taste for saving

It is often argued that "taste for saving" (Cagan, 1965) is distributed heterogeneously in the population: some individuals derive utility from saving, even without a clear economic motive, whereas others simply do not save at all. Although these ad-hoc statements are at odds with the model presented above, in the empirical analysis we can try to separate those which like to save from those that dislike saving. For this, I include a variable whether or not the head of household declares to be a "saver", which is based on the following stated preferences question from the DHS:

Question 3.4. *Please indicate what you do with money that is left over after having paid for food, rent, and other necessities, on a scale from 1 to 7, where 1 means "I like to spend all my money immediately" and 7 means "I want to save as much as possible"*

[16] A second condition is that the mean and standard deviation of the replacement rate should be negatively correlated, but this is true by construction, as we subtract the (squared) mean from the second moment to compute the variance of the replacement rate.

[17] The coefficient estimates for the 75th quantile of μ and σ are significant at the 11% level, and for the 80th quantile at the conventional 5% level.

The indicator Saver is coded 1 if the respondent answers 6 or 7. The variable Saver is additionally interacted with μ and σ to allow for different effects between stated savers and non-savers[18], and hopefully capture the unobservable "taste for saving". Table 3.5 below shows the results.[19]

The coefficient on the interaction term between μ and Saver is negative across the entire distribution, and significantly so from the median upwards, indicating that the stated savers more strongly displace private saving by pension saving. In the higher quantiles, the difference between the estimated displacement effect for savers and non-savers is the largest; focusing only on non-savers, one would conclude that pensions do not affect private saving; for savers, I find either no effect or a significantly negative effect. The magnitude of the estimate suggests that for the highest (90^{th}) quantile, an increase in the replacement rate by 1 percentage point leads to a decrease in the private saving rate by 1.9 percentage point.

The precautionary pension saving effect shows a similar pattern; only for the highest quantiles there is evidence of precautionary saving due to pension income uncertainty, and the effect is stronger for the savers than for the non-savers. For the lower quantiles, the effect on saving is not significant. Of course, these households save little (or negative) compared to the higher quantiles, and hence there saving behavior may be related to other factors, such as the credit constraints mentioned in Section 3.3.1. Similarly, lifespan uncertainty is found to decrease saving significantly for the lowest quantiles, contrary to the lifecycle model.

The dummy Saver has a (weakly) significant positive effect on the saving rate, as expected. The remaining parameter estimates are very similar to those in Table 3.3. All in all, I conclude that those in the highest conditional quantiles are more likely to behave according to the lifecycle model, as these households displace private saving with retirement income and increase saving with uncertainty over pension income and lifespan.

[18] Note that the question elicits saving preferences or saving intentions, which is correlated with but remains different from actual saving behavior (see, for instance, Laibson et al. (1998)).

[19] Results using a different saving preference indicator, based on the question "Will you adjust your conduct if pensions are cut down, for example through an adjustment on the indexation, postponement of the retirement age or a different pension system?", are qualitatively and quantitatively similar and are available upon request.

Table 3.5. Results saving equation with interaction terms, weighted quantile regressions

	Quantile (10%)	(25%)	(50%)	(75%)	(90%)
μ	0.473*	-0.108	-0.0854	-0.156	-0.773*
	(0.261)	(0.134)	(0.109)	(0.181)	(0.432)
$\mu \times$ Saver	-0.068	-0.152	-0.312**	-0.662***	-1.121***
	(0.230)	(0.0963)	(0.149)	(0.238)	(0.433)
σ	-0.273	0.132	0.187**	0.278**	0.520*
	(0.250)	(0.0981)	(0.0820)	(0.163)	(0.293)
$\sigma \times$ Saver	-0.087	0.142	0.430***	0.676***	0.781*
	(0.281)	(0.208)	(0.163)	(0.212)	(0.441)
Survival	-2.541***	-1.194***	0.135	1.010**	2.568***
	(0.523)	(0.270)	(0.276)	(0.466)	(1.024)
Secondary educated	-0.322***	-0.198***	-0.0465	-0.225***	-1.006***
	(0.121)	(0.0520)	(0.0368)	(0.0784)	(0.272)
Higher educated	0.528***	0.147***	0.169***	0.112	-0.0806
	(0.110)	(0.0534)	(0.0354)	(0.0793)	(0.301)
University educated	0.113	0.218***	0.199***	0.0402	-0.0512
	(0.196)	(0.0732)	(0.0477)	(0.0962)	(0.314)
Female	-1.823***	-0.535***	-0.0761*	-0.174***	0.0817
	(0.141)	(0.0613)	(0.0445)	(0.0618)	(0.143)
Partner	-0.579***	-0.452***	-0.0116	0.171**	1.273***
	(0.118)	(0.0545)	(0.0386)	(0.0830)	(0.180)
Log(Nr children+1)	0.278***	0.105**	-0.0886***	-0.245***	-0.719***
	(0.107)	(0.0460)	(0.0290)	(0.0511)	(0.148)
Civil servant	-0.467***	-0.285***	-0.109***	-0.159***	0.0909
	(0.131)	(0.0570)	(0.0315)	(0.0585)	(0.165)
No permanent contract	0.432	-0.0385	0.173*	0.0800	0.388**
	(0.411)	(0.266)	(0.0923)	(0.0971)	(0.186)
Home owner	0.0356	0.0764*	0.0888**	-0.00233	0.171
	(0.102)	(0.0453)	(0.0369)	(0.0768)	(0.191)
Saver	-0.183	0.0952**	0.208*	0.216*	0.336
	(0.197)	(0.0398)	(0.112)	(0.129)	(0.246)
Urban area	0.339***	0.0275	0.0653**	0.0375	0.253*
	(0.0969)	(0.0447)	(0.0306)	(0.0553)	(0.147)
Bad health	-0.736*	-0.192	-0.249	-0.235	-2.142***
	(0.413)	(0.457)	(0.237)	(0.148)	(0.301)
Constant	-1.707***	0.0866	0.378***	1.199***	3.525***
	(0.377)	(0.170)	(0.105)	(0.193)	(0.488)
Observations	1010	1010	1010	1010	1010
Households	491	491	491	491	491

Cluster-bootstrapped standard errors in parentheses; 1000 replications
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Time effects included, not reported

3.5.2 A panel data quantile regression model

Finally, I estimate a panel data model for quantile regressions, where the (random) household effect α_i is parameterized as the mean of the time-varying independent variables, following Mundlak (1978); see also Abrevaya and Dahl (2008) and Wooldridge (2010).[20] To obtain a pure location-shift approach (i.e. the household effect does not vary over the quantiles), I impose cross-quantile equality restrictions on the estimates of the household effects. Table 3.6 shows the parameter estimates of the weighted quantile regression estimates of equation 3.7b.

The parameter estimates and significance levels are similar to the results obtained without the correlated random effects (Table 3.3), even while the household effects are jointly significant ($p = 0.000$), suggesting that the estimates of the displacement effect and precautionary saving effects are not biased due to unobserved time-invariant heterogeneity. The differences are a somewhat smaller (in absolute value) estimated displacement effect, and a slightly larger precautionary saving effect, which is significant for the non-savers only at the median, and for the savers in the highest quantiles. The remaining coefficients for the explanatory variables are similar to Tables 3.3 and 3.5 as well.

[20] Alternative approaches for fixed-effects quantile regression include penalized quantile regression approaches, as in Koenker (2004) and Lamarche (2010), in which a full set of individual dummies is included, which are subject to shrinkage towards a common value to prevent the well-known incidental parameters problem. However, the degree of shrinkage influences the parameter estimates of all explanatory variables, and is subject to ongoing research. Hence, I prefer to use the conceptually straightforward Mundlak (1978) approach.

Table 3.6. Results saving equation with correlated random effects, weighted quantile regressions

	Quantile (10%)	(25%)	(50%)	(75%)	(90%)
μ	0.867	0.329	0.069	-0.465*	-0.789**
	(0.585)	(0.281)	(0.164)	(0.245)	(0.391)
$\mu \times$ Saver	-0.224	-0.182	-0.413***	-0.628***	-0.702**
	(0.291)	(0.155)	(0.156)	(0.203)	(0.341)
σ	0.246	-0.276*	0.425***	0.121	0.430
	(0.470)	(0.157)	(0.162)	(0.251)	(0.528)
$\sigma \times$ Saver	0.657	0.088	0.235	0.872**	1.386**
	(0.515)	(0.185)	(0.196)	(0.414)	(0.673)
Survival	-2.352***	-0.659*	-0.550	1.074**	1.963***
	(1.000)	(0.364)	(0.446)	(0.487)	(0.668)
Secondary educated	-0.364***	-0.267***	-0.170***	-0.187**	-0.985***
	(0.139)	(0.0616)	(0.0457)	(0.0883)	(0.340)
Higher educated	0.295***	0.195***	0.0944**	0.0487	-0.158
	(0.114)	(0.0579)	(0.0417)	(0.0922)	(0.372)
University educated	0.296	0.201**	0.0392	-0.0236	-0.306
	(0.186)	(0.0793)	(0.0556)	(0.115)	(0.379)
Female	-1.665***	-0.489***	-0.139***	0.000239	0.383**
	(0.140)	(0.0649)	(0.0474)	(0.0716)	(0.155)
Partner	-0.384	-0.243	-0.284	-0.325	-0.960
	(1.209)	(1.011)	(0.762)	(0.417)	(1.092)
Log(Nr children+1)	-0.171	-0.321	0.0354	-0.186	-0.305
	(0.465)	(0.208)	(0.165)	(0.197)	(0.585)
Civil servant	0.290	-0.670***	-0.619***	-0.816***	-1.422***
	(0.543)	(0.188)	(0.127)	(0.227)	(0.544)
No permanent contract	1.606***	0.247	-0.0469	-0.307**	-1.068***
	(0.508)	(0.253)	(0.130)	(0.141)	(0.278)
Home owner	1.228**	0.200	0.861***	0.207	1.537**
	(0.510)	(0.271)	(0.248)	(0.316)	(0.719)
Saver	0.0213	0.125*	0.168*	0.302*	0.487**
	(0.097)	(0.0742)	(0.094)	(0.156)	(0.224)
Urban area	-1.805***	-0.365	0.944**	1.134***	3.603***
	(0.700)	(0.475)	(0.394)	(0.391)	(0.740)
Bad health	-1.219**	-0.334	-0.0382	0.201	-1.297***
	(0.563)	(0.407)	(0.189)	(0.223)	(0.452)
$\overline{\mu}$	-0.512**	-0.512**	-0.512**	-0.512**	-0.512**
	(0.208)	(0.208)	(0.208)	(0.208)	(0.208)
$\overline{\mu \times \text{Saver}}$	0.169	0.169	0.169	0.169	0.169
	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
$\overline{\sigma}$	0.541**	0.541**	0.541**	0.541**	0.541**
	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)
$\overline{\sigma \times \text{Saver}}$	0.338	0.338	0.338	0.338	0.338
	(0.268)	(0.268)	(0.268)	(0.268)	(0.268)
$\overline{\text{Survival}}$	0.811	0.811	0.811	0.811	0.811
	(0.765)	(0.765)	(0.765)	(0.765)	(0.765)
$\overline{\text{Partner}}$	-0.283	-0.283	-0.283	-0.283	-0.283
	(0.434)	(0.434)	(0.434)	(0.434)	(0.434)
$\overline{\text{log Nr Children+1}}$	0.418*	0.418*	0.418*	0.418*	0.418*
	(0.216)	(0.216)	(0.216)	(0.216)	(0.216)
$\overline{\text{Civil Servant}}$	0.588***	0.588***	0.588***	0.588***	0.588***
	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)
$\overline{\text{No permanent contract}}$	0.772***	0.772***	0.772***	0.772***	0.772***
	(0.231)	(0.231)	(0.231)	(0.231)	(0.231)
$\overline{\text{Home owner}}$	-0.756***	-0.756***	-0.756***	-0.756***	-0.756***
	(0.256)	(0.256)	(0.256)	(0.256)	(0.256)

Continued on next page

Table 3.6 – continued from previous page

	Quantile (10%)	(25%)	(50%)	(75%)	(90%)
$\overline{\text{Saver}}$	0.227***	0.227***	0.227***	0.227***	0.227***
	(0.0580)	(0.0580)	(0.0580)	(0.0580)	(0.0580)
$\overline{\text{Urban area}}$	0.456	0.456	0.456	0.456	0.456
	(0.474)	(0.474)	(0.474)	(0.474)	(0.474)
$\overline{\text{Bad health}}$	-0.890**	-0.890**	-0.890**	-0.890**	-0.890**
	(0.364)	(0.364)	(0.364)	(0.364)	(0.364)
Constant	-0.861*	-0.565***	0.538***	2.038***	3.481***
	(0.456)	(0.201)	(0.143)	(0.233)	(0.691)
Observations	1010	1010	1010	1010	1010
Households	491	491	491	491	491
p-value test Mundlak terms	0.000	0.000	0.000	0.000	0.000

Cluster-bootstrapped standard errors in parentheses; 1000 replications
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Time effects included, not reported

3.5.3 Linear models

A final concern may be the degree of structure imposed on the data, in particular the non-linear effects in age and the expected retirement date, the composition of the dependent variable as well as the weighting procedure used to correct for sample selection effects. Therefore, I impose less structure to investigate whether or not the results are created artificially. In particular, I set $\alpha = R = 1$, and use either the level of saving or the saving rate as dependent variables below. Table 3.7 shows the results from using a random effects approach (RE) and a fixed effects approach (FE). Moreover, I also use a Heckman model, with the same selection equation as used above.[21] Of course, if sample selection effects or measurement errors are really points of concern, the results shown below should be interpreted with caution.

The results indicate that the displacement effect is significantly negative using RE or a Heckman model when the level of saving is used as dependent variable, and only for the Heckman model using the saving rate. The precautionary effect is positive and significantly different from zero for most specifications, except when using the Heckman model for the saving rate. The effect of longer expected survival is significantly positive. To sum up, while the results are more mixed using

[21] For both dependent variables, the exclusion restrictions are on the variables describing violations for other probabilistic questions, as well as on the lagged dependent variable in the selection equation. These variables jointly significant ($p = 0.000$) for the selection equation, and the estimated correlation between the error terms is significantly negative at the 5% level.

Table 3.7. Results saving equation, linear models

	Saving			Saving rate		
	RE	FE	Heckman	RE	FE	Heckman
μ	-11.68**	-3.515	-9.295**	-0.0114	0.0228	0.0574*
	(4.889)	(5.092)	(4.613)	(0.0202)	(0.0215)	(0.0330)
σ	14.16***	12.88***	4.592	0.0654***	0.0670***	0.0460**
	(4.681)	(4.829)	(9.452)	(0.0195)	(0.0206)	(0.0213)
Survival	91.90***	105.3***	43.29*	0.350***	0.461***	0.163*
	(15.42)	(16.54)	(24.79)	(0.0641)	(0.0709)	(0.0886)
Observations	1010	1010	2148	1010	1010	2148
Households	491	491	1013	491	491	1013

Panel-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Same control variables as in Table 3.3, as well as age and its square, lagged financial wealth and future income
The Heckman selection equation has the same variables as used in Table 3.2

the linear models or a simpler Heckman model, the main effects prevail in most specifications, suggesting that the weighting, the construction of the composite dependent variable and the non-linear age effects, all used in the quantile regressions, are not driving the main results.

3.6 Conclusion

In this paper I show evidence of displacement of private saving by pension saving, as well as precautionary saving due to uncertain lifespan and uncertainty over pension income, for a sample of Dutch households. The estimated saving equation is based on a lifecycle model featuring rational individuals that work and consume or save before retirement; income after retirement income is uncertain from today's perspective, as is remaining life expectancy. I use the answers from subjective probabilistic survey questions to compute expected pension income and the standard deviation of pension income as a measure for uncertainty, as well as the subjective survival curve. Therefore, the subjective expectations vary between households, and within households over time. Quantile regression results show that, for the more affluent respondents, saving increases with the uncertainty in pension income and increase with expected length of life, as predicted by the theory. The displacement effect is significant for the higher quantiles as well, and shows that pensions crowd out private saving, especially for those that state to have a preference for saving for retirement. These results are robust to the inclusion of correlated random household effects, and are in line with the predictions from a version of the lifecycle model with liquidity constraints and retirement income uncertainty. Compared to the empirical literature, the obtained displacement effect, measured as the increase in private wealth due to a 1 Euro decrease in pension wealth, is rather low, at 11.5%. It is consistent with earlier literature for the Netherlands, however. Moreover, I find that ignoring precautionary saving motives leads to an estimated crowding out effect which is too high, a feature which is likely to hold in the previous empirical literature based on certainty equivalence as well.

For policy purposes, the paper suggests that Dutch employees do prepare for retirement, as indicated by the expected sign for pension uncertainty and mortality risk. However, for the less affluent part of the sample, these effects are not found. Liquidity constraints may indeed be an explanation for this finding, although time-inconsistent preferences or financial illiteracy are likely to play a role as well, as argued by, amongst others, Choi et al. (2011) and Alessie et al. (2011b).

In future research, allowing for endogenous labor supply and retirement is the obvious next step, but the expectations data collected thus far are not sufficient at this moment. Moreover, if utility is assumed to be separable in consumption and leisure, the impact of endogenous retirement is likely to be small. At the least, the subjective pension income expectations are shown to yield plausible results regarding saving behavior of the currently young population. Bigger samples and better ways to elicit expectations, for instance using the procedure of Delavande and Rohwedder (2008), may increase the explanatory power of these subjective expectations.

3.A Derivation of equation 3.2

The problem the individual faces is to maximize lifecycle utility subject to the consolidated lifetime budget constraint. Formally, I write the problem as

$$\max_{c_\tau} \sum_{\tau=t}^{K-1} \beta^{\tau-t} U(c_\tau) + E_t \sum_{\tau=K}^{L} \beta^{\tau-t} a_\tau U(c_\tau) \tag{3.A.1a}$$

$$\text{s.t.} \sum_{\tau=t}^{K-1} R^{t-\tau} c_\tau + \sum_{\tau=K}^{L} R^{t-\tau} c_\tau = RA_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau + \sum_{\tau=K}^{L} R^{t-\tau} y_K, \tag{3.A.1b}$$

where c_τ is consumption in period τ and E_t is the expectation operator conditional on information available in period t. I solve for today's consumption, c_t, in three steps. First, I solve the retirement stage and calculate the value of future utility streams, conditional on net worth available at the beginning of retirement, A_{K-1}. Second, I solve the problem for the working stage, and compute the value of utility conditional on leaving A_{K-1} available for future consumption. Finally, I choose A_{K-1} to maximize lifecycle utility.

3.A.1 Consumption during retirement

During retirement, when the uncertainty over pension income has resolved, the problem can be written as

$$\max_{c_\tau} \sum_{\tau=K}^{L} \beta^{\tau-K} a_\tau U(c_\tau) \tag{3.A.2a}$$

$$\text{s.t.} \sum_{\tau=K}^{L} R^{K-\tau} c_\tau = RA_{K-1} + \sum_{\tau=K}^{L} R^{K-\tau} y_K \tag{3.A.2b}$$

$$A_\tau = RA_{\tau-1} + y_\tau - c_\tau \tag{3.A.2c}$$

$$A_L = 0. \tag{3.A.2d}$$

For $(K \leq \tau \leq L)$, the solutions are given by[22]

$$c_\tau = \frac{\log(a_\tau)}{\alpha} + c_K \tag{3.A.3a}$$

[22] I use the first-order condition, the consolidated retirement budget constraint (3.B.6) and the terminal condition (3.B.8).

$$c_K = -\frac{1}{\alpha \sum_{\tau=K}^{L} R^{L-\tau}} \sum_{\tau=K}^{L} R^{L-\tau} \log\left(a_\tau\right) + \frac{R^{L-K+1}}{\sum_{\tau=K}^{L} R^{L-\tau}} A_{K-1} + y_K. \tag{3.A.3b}$$

For convenience I define

$$\Pi = -\frac{1}{\alpha \sum_{\tau=K}^{L} R^{L-\tau}} \sum_{\tau=K}^{L} R^{L-\tau} \log\left(a_\tau\right),$$

so that I can write for $K \leq q \leq L$[23]

$$c_q = \frac{\log\left(a_q\right)}{\alpha} + \Pi + \frac{R^{L-K+1}}{\sum_{\tau=K}^{L} R^{L-\tau}} A_{K-1} + y_K. \tag{3.A.4}$$

The value of utility after retirement can then be written as

$$\begin{aligned}\sum_{q=K}^{L} \beta^{q-t} a_q U\left(c_q\right) &= -\frac{1}{\alpha} \exp\left[-\alpha\left(\Pi + \frac{R^{L-K+1}}{\sum_{\tau=K}^{L} R^{L-\tau}} A_{K-1}\right)\right] \\ &\quad \cdot \exp\left[-\alpha y_K\right] \sum_{q=K}^{L} \beta^{q-t} a_q \exp\left[-\alpha\left(\frac{\log\left(a_q\right)}{\alpha}\right)\right] \\ &= -\frac{1}{\alpha} \exp\left[-\alpha\left(\Pi + \frac{R^{L-K+1}}{\sum_{\tau=K}^{L} R^{L-\tau}} A_{K-1}\right)\right] \cdot \exp\left[-\alpha y_K\right] \cdot \frac{\sum_{q=K}^{L} R^{-q}}{\beta^t},\end{aligned} \tag{3.A.5}$$

which is a function of the state variable A_{K-1}.

3.A.2 Consumption during working life

For the working period $(t \leq \tau \leq K-1)$ the problem reads

$$\max_{c_\tau} \sum_{\tau=t}^{K-1} \beta^{\tau-t} U\left(c_\tau\right) \tag{3.A.6a}$$

$$\text{s.t.} \sum_{\tau=t}^{K-1} R^{t-\tau} c_\tau = R A_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau - R^{t-K+1} A_{K-1}. \tag{3.A.6b}$$

The solution for the consumption path during working life is given by

$$c_\tau = c_t \tag{3.A.7a}$$

[23] Note that I assumed that a_K=1, so that the solution for c_K is still as in (3.A.3b).

$$c_t = \frac{RA_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau - R^{t-K+1} A_{K-1}}{\sum_{\tau=t}^{K-1} R^{t-\tau}}. \tag{3.A.7b}$$

The value of utility during the working stage can be written as

$$\sum_{\tau=t}^{K-1} \beta^{\tau-t} U(c_\tau) = -\frac{1}{\alpha} \sum_{\tau=t}^{K-1} \beta^{\tau-t} \exp[-\alpha c_\tau] = -\frac{\exp[-\alpha c_t]}{\alpha} \sum_{\tau=t}^{K-1} R^{t-\tau}, \tag{3.A.8}$$

which is also a function of the wealth stock to be used during retirement, A_{K-1}.

3.A.3 Lifecycle consumption

Finally, I choose A_{K-1} to optimize the lifecycle utility function (3.A.1a) using (3.A.8) and (3.A.5) subject to the constraint (3.A.7b). The first-order condition for A_{K-1} gives

$$A_{K-1} = \frac{\sum_{\tau=K}^{L} R^{L-\tau}}{R^{L-K+1}} \left(c_t - \Pi + \frac{\log\left(E_t\left(\exp\left[-\alpha y_K\right]\right)\right)}{\alpha} \right).$$

Use the constraint (3.A.7b) and plug in Π to obtain

$$c_t = \frac{RA_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau}{\sum_{\tau=t}^{L} R^{t-\tau}} - \frac{1}{\alpha} \frac{\sum_{\tau=K}^{L} R^{L-\tau} \log\left(a_\tau\right)}{\sum_{\tau=t}^{L} R^{L-\tau}} - \frac{\sum_{\tau=K}^{L} R^{L-\tau}}{\sum_{\tau=t}^{L} R^{L-\tau}} \left(\frac{\log\left(E_t\left(\exp\left[-\alpha y_K\right]\right)\right)}{\alpha} \right).$$

The final task is to obtain an expression for $\log\left(E_t\left(\exp\left[-\alpha y_K\right]\right)\right)$. For any random variable x,

$$M(\gamma) = E\left(\exp[\gamma x]\right)$$

represents the moment-generating function. For the case that $y_K \sim \mathcal{N}(\mu, \sigma)$, I have that $M(\gamma) = \exp[\mu\gamma] \exp[\sigma^2\gamma^2/2]$, so that I can write

$$\log\left(E_t(\exp\left[-\alpha y_K\right])\right) = -\alpha\mu + \frac{1}{2}\sigma^2\alpha^2. \tag{3.A.9}$$

Using this result and simplifying the remaining terms, setting $r = \rho$,I end up with equation (3.2):

$$c_t = \frac{RA_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau + \sum_{\tau=K}^{L} R^{t-\tau}\mu}{\sum_{\tau=t}^{L} R^{t-\tau}} - \frac{\sum_{\tau=K}^{L} R^{t-\tau}\left(\frac{1}{\alpha}\log\left(a_\tau\right) + \frac{1}{2}\alpha\sigma^2\right)}{\sum_{\tau=t}^{L} R^{t-\tau}}. \tag{3.A.10}$$

This is equation 3.2.

3.B Incorporating a liquidity constraint

Suppose that at some date $v < K-1$ the constraint binds, and that $A_{t-1} > 0$. Then the problem before retirement is

$$\max_{c_\tau} -\frac{1}{\alpha}\sum_{\tau=t}^{v}\beta^{\tau-t}\exp\left[-\alpha c_\tau\right] - \frac{1}{\alpha}\sum_{\tau=v+1}^{K-1}\beta^{\tau-t}\exp\left[-\alpha y_\tau\right] \tag{3.B.1}$$

$$\text{s.t.} \sum_{\tau=t}^{v} R^{t-\tau} c_\tau = RA_{t-1} + \sum_{\tau=t}^{v} R^{t-\tau} y_\tau. \tag{3.B.2}$$

I know from equation 3.A.7b in Appendix 3.A that the solution for current consumption must equal

$$c_t = \frac{RA_{t-1} + \sum_{\tau=t}^{v} R^{t-\tau} y_\tau}{\sum_{\tau=t}^{v} R^{t-\tau}}. \tag{3.B.3}$$

In general, there exists no closed-form solution for the date v at which the liquidity constraint becomes binding. Furthermore, in a discrete-time setting, minimizing consumption with respect to time $\left(\frac{dc_t}{dv}\right)$ is not a valid approach, since dv never approaches zero. Still, I proceed in this manner, as the intuition carries over directly to the case of discrete differences, but is computationally more attractive for characterizing the complete solution. I admit that I make an approximation error of order $O(1)$.

Given these limitations, I minimize period t consumption to find the date v:

$$\begin{aligned}\frac{\partial c_t}{\partial v} = {} & \frac{\left(-R^{t-v}\log\left(R\right) y_v + R^{t-v}\frac{\partial y_v}{\partial v}\right)\sum_{\tau=t}^{v} R^{t-\tau}}{\left(\sum_{\tau=t}^{v} R^{t-\tau}\right)^2} \\ & + \frac{R^{t-v}\log\left(R\right)\left(RA_{t-1} + \sum_{\tau=t}^{v} R^{t-\tau} y_\tau\right)}{\left(\sum_{\tau=t}^{v} R^{t-\tau}\right)^2} = 0.\end{aligned}$$

Simplifying gives

$$\left(\log(R)\, y_v + \frac{\partial y_v}{\partial v}\right) \sum_{\tau=t}^{v} R^{t-\tau} - \log(R) \sum_{\tau=t}^{v} R^{t-\tau} y_\tau = \log(R)\, R A_{t-1}.$$

There is no closed form solution for the exact date v, but note that for a concave time path of income, with $\partial y_v / \partial v > 0$ and $\partial^2 y_v / \partial v^2 < 0$,

$$\frac{dv}{dA_{t-1}} = \frac{R \log(R)}{\left(\log(R) \frac{\partial y_v}{\partial v} - \frac{\partial^2 y_v}{\partial v^2}\right) \sum_{\tau=t}^{v} R^{t-\tau}} > 0. \tag{3.B.4}$$

Under the assumption that the liquidity constraint is always binding[24] this suffices for current consumption. Concluding, c_t is independent of A_{K-1} and hence of μ, σ^2 and survival probabilities.

If the level of current wealth is large, and/or the income path is increasing, the constraint will not bind before retirement. If the constraint binds after retirement, the problem after retirement can be stated as follows:

$$\max_{c_\tau} \sum_{\tau=K}^{v} \beta^{\tau-K}(a_\tau) U(c_\tau) \tag{3.B.5}$$

$$\text{s.t.} \sum_{\tau=K}^{v} R^{K-\tau} c_\tau = R A_{K-1} + \sum_{\tau=K}^{v} R^{K-\tau} y_K \tag{3.B.6}$$

$$A_\tau = R A_{\tau-1} + y_\tau - c_\tau. \tag{3.B.7}$$

$$A_v = 0 \tag{3.B.8}$$

I know from equation 3.A.3b that the solution to this problem in period K equals

$$c_K = -\frac{\sum_{\tau=K}^{v} R^{t-\tau} \log(a_\tau)}{\alpha \sum_{\tau=K}^{v} R^{t-\tau}} + \frac{R^{t-K+1}}{\sum_{\tau=K}^{v} R^{t-\tau}} A_{K-1} + y_K. \tag{3.B.9}$$

I minimize period K consumption to find the date v:

$$\begin{aligned}\frac{\partial c_K}{\partial v} = {} & \frac{R^{t-v} \log(R) \log(a_v)}{\alpha \sum_{\tau=K}^{v} R^{t-\tau}} - \frac{\frac{\partial a_v}{\partial v} R^{t-v}}{\alpha a_v \sum_{\tau=K}^{v} R^{t-\tau}} \\ & - \frac{R^{t-v} \log(R) \sum_{\tau=K}^{v} R^{t-\tau} \log(a_\tau)}{\alpha \left(\sum_{\tau=K}^{v} R^{t-\tau}\right)^2} + \frac{R^{t-v} \log(R)\, R^{1-K} A_{K-1}}{\left(\sum_{\tau=K}^{v} R^{t-\tau}\right)^2} = 0.\end{aligned}$$

[24] This is not unreasonable under the same concavity assumption for income, as v is already chosen as far away in the future as possible depending on the level of A_{t-1}, see (3.B.4).

Simplifying this FOC yields the implicit solution for v:

$$\log(R)\log(a_v)\sum_{\tau=K}^{v}R^{-\tau}-\frac{\frac{\partial a_v}{\partial v}\sum_{\tau=K}^{v}R^{-\tau}}{a_v}-\log(R)\sum_{\tau=K}^{v}R^{-\tau}\log(a_\tau)$$
$$=-\alpha\log(R)R^{1-K}A_{K-1}. \tag{3.B.10}$$

There is no closed form solution for the date v, but I can gain more insight by taking the total differential of the expression above, and solving for the effect of A_{K-1} on v:

$$\frac{dv}{dA_{K-1}}=\frac{\alpha\log(R)R^{1-K}}{\left(\frac{\partial^2 a_v}{\partial v^2}-\frac{\partial a_v}{\partial v}\log(R)a_v-\left(\frac{\partial a_v}{\partial v}\right)^2\right)\sum_{\tau=K}^{v}R^{-\tau}}.$$

The sign of this expression depends on the structure on the survival function:

$$\frac{dv}{dA_{K-1}}>0\Longleftrightarrow H\equiv\frac{\partial^2 a_v}{\partial v^2}-\frac{\partial a_v}{\partial v}\log(R)a_v-\left(\frac{\partial a_v}{\partial v}\right)^2>0. \tag{3.B.11}$$

After period v, the optimal consumption pattern simply equals the (realized) value of pension income, as the possibility of death makes the agent impatient. The value of consumption after retirement can now be written as

$$-\frac{E_t\exp[-\alpha c_K]}{\alpha}\sum_{\tau=K}^{v}R^{t-\tau}-\frac{E_t\exp[-\alpha y_K]}{\alpha}\sum_{\tau=v+1}^{L}R^{t-\tau}(a_\tau),$$

with c_K given by (3.B.9) and v implicitly by (3.B.10)

The working stage has not changed, so I immediately infer that

$$c_t=\frac{RA_{t-1}+\sum_{\tau=t}^{K-1}R^{t-\tau}y_\tau-R^{t-K+1}A_{K-1}}{\sum_{\tau=t}^{K-1}R^{t-\tau}},$$

and the value of pre-retirement consumption equals

$$-\frac{1}{\alpha}\sum_{\tau=t}^{K-1}\beta^{\tau-t}\exp[-\alpha c_\tau]=-\frac{\exp[-\alpha c_t]}{\alpha}\sum_{\tau=t}^{K-1}R^{t-\tau}.$$

The lifecycle value value function equals

$$-\frac{\exp[-\alpha c_t]}{\alpha}\sum_{\tau=t}^{K-1}R^{t-\tau}-\frac{E_t\exp[-\alpha c_K]}{\alpha}\sum_{\tau=K}^{v}R^{t-\tau}-\frac{E_t\exp[-\alpha y_K]}{\alpha}\sum_{\tau=v+1}^{L}R^{t-\tau}(a_\tau).$$

The value function depends on A_{K-1}, both directly, via c_t and c_K, and indirectly, due to it's effect on v. I choose wealth for retirement by maximizing the value function, as in the unconstrained case in Appendix 3.A. I use the fact that $v = \arg\min c_K$ to infer that $\partial c_K / \partial A_{K-1}$ equals the direct effect of A_{K-1} on period K consumption, that is, $\partial c_K / \partial A_{K-1} = R^{t-K+1} / \sum_{\tau=K}^{v} R^{t-\tau}$.
The FOC for A_{K-1} equals

$$E_t \exp\left[-\alpha c_K\right] R^{t-K+1} + \frac{\partial v}{\partial A_{K-1}} R^{-v} \log\left(R\right) \frac{E_t \exp\left[-\alpha c_K\right]}{\alpha} = \exp\left[-\alpha c_t\right] R^{t-K+1}.$$

Plugging in c_K gives

$$\begin{aligned} &\exp\left[\frac{\sum_{\tau=K}^{v} R^{t-\tau} \log\left(a_\tau\right)}{\sum_{\tau=K}^{v} R^{t-\tau}}\right] \exp\left[-\frac{\alpha R^{t-K+1} A_{K-1}}{\sum_{\tau=K}^{v} R^{t-\tau}}\right] E_t \exp\left[-\alpha y_K\right] \\ &\cdot \left(R^{t-K+1} + \frac{\partial v}{\partial A_{K-1}} \frac{R^{-v} \log\left(R\right)}{\alpha}\right) = \exp\left[-\alpha c_t\right] R^{t-K+1}. \end{aligned}$$

The solution for A_{K-1} equals

$$\begin{aligned} A_{K-1} = &\frac{\sum_{\tau=K}^{v} R^{t-\tau} \log\left(a_\tau\right)}{\alpha R^{t-K+1}} - \frac{\sum_{\tau=K}^{v} R^{t-\tau}\left(\mu - \alpha\sigma^2\right)}{R^{t-K+1}} + \frac{\sum_{\tau=K}^{v} R^{t-\tau} c_t}{R^{t-K+1}} \\ &+ \frac{\sum_{\tau=K}^{v} R^{t-\tau} \log\left(R^{t-K+1} + \frac{\partial v}{\partial A_{K-1}} \frac{R^{-v}\log(R)}{\alpha}\right)}{\alpha R^{t-K+1}} - \frac{\sum_{\tau=K}^{v} R^{t-\tau} \log\left(R^{t-K+1}\right)}{\alpha R^{t-K+1}}. \end{aligned} \tag{3.B.12}$$

And the solution for current consumption is equal to

$$\begin{aligned} c_t = &\frac{R A_{t-1} + \sum_{\tau=t}^{K-1} R^{t-\tau} y_\tau + \sum_{\tau=K}^{v} R^{t-\tau} \mu}{\sum_{\tau=t}^{v} R^{t-\tau}} - \frac{\sum_{\tau=K}^{v} R^{t-\tau}\left(\frac{1}{\alpha}\log\left(a_\tau\right) + \alpha\sigma^2\right)}{\sum_{\tau=t}^{v} R^{t-\tau}} \\ &- \frac{\sum_{\tau=K}^{v} R^{t-\tau} \log\left(\frac{H\sum_{\tau=K}^{v} R^{t-\tau} + (\log(R))^2 R^{-v}}{H\sum_{\tau=K}^{v} R^{t-\tau}}\right)}{\alpha \sum_{\tau=t}^{v} R^{t-\tau}}, \end{aligned} \tag{3.B.13}$$

with H defined in (3.B.11).

3.C Forecasting household income

As saving decreases with future (labor) income, I need an estimate of household income until the retirement age to control for this effect in the saving rate equation. For this purpose, I employ the waves of 1996 until 2011 of the DHS to estimate a model for household income. I employ a parsimonious model with age and household composition as the only explanatory variables. More specifically, I estimate

$$\log\left(y_{it}\right) = m\left(age_{it}\right) + h_{it} + u_i + \epsilon_{it}$$

where $m\left(age_{it}\right)$ is a linear spline function with knots at 30, 35, 40, 45, 50, 55 and 60 years of age, h_{it} the (time-varying) number of persons in the family, u_i is a household fixed effect and ϵ_{it} a random error term. This equation is combined with an equation for predicting the number of persons in the family, which is regressed on the same age spline and a household fixed effect. The sample is restricted to household heads aged 25 until 70. I experimented with different parameter estimates by education group and inserting Deaton and Paxson (1994)-type of orthogonalized time effects, but this does not affect the results. The results are shown in table 3.C.1.

Table 3.C.1. Fixed effects model for log income

Age	Coefficient	Standard error
26-30	0.0668***	(0.00973)
31-35	0.0215***	(0.00584)
36-40	0.0304***	(0.00482)
41-45	0.0278***	(0.00535)
46-50	0.0202***	(0.00436)
51-55	0.00364	(0.00497)
56-60	0.00405	(0.00507)
61^+	-0.00189	(0.00549)
# Persons	0.0300***	(0.00974)
Constant	9.212***	(0.0712)
Observations	25678	
Number of households	7483	
R^2	0.024	
σ_u	0.522	
σ_ϵ	0.384	
p-value Age effects	0.000	

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Household income is increasing rapidly for young household heads (± 6% per year), and income growth is decreasing with age until the age path is essentially flat after age 50. Using these parameter estimates, the forecast of household income at age $t+s$ is calculated as

$$\widehat{y_{it+s}} = \exp\left[m\left(\widehat{age_{it+s}}\right) + \widehat{h_{it+s}} + \widehat{u}_i + z\right]$$

where z is a random draw from the normal distribution with mean zero and standard deviation $0.5 * \widehat{\sigma_\epsilon}$. The scaling factor of 0.5 is in line with Knoef et al. (2009), who estimate a similar model using administrative data from Statistics Netherlands, and obtain an estimate of σ_ϵ of 0.205. Their estimate of the variance of the error term is smaller due to using tax-records data, which are less likely to suffer from measurement error as the survey data I employ. Note that I use forecasted income as a left-hand-side variable in the main regressions to limit the effect of measurement error in the estimate of future income.

Chapter 4

Demand for Annuities: A Multivariate Binary Response Model with Misclassification*

* This chapter is based on Alessie, Kalwij and Van Santen (2012)..

4.1 Introduction

Annuities are theoretically superior to hedge against longevity risk. As shown by Yaari (1965), when length of life is random, the agent should annuitize all his wealth and consume out of the stream of money the annuity delivers, in order to ensure dying with zero wealth. Yet, in practice, the degree of annuitization has often been found to be low, an empirical phenomenon referred to as the 'Annuity Puzzle'. Many reasons have been mentioned to explain this puzzle, some of which are listed here. First, the result of Yaari (1965) is derived under some restrictive assumptions, such as actuarially fair annuities and absence of other uncertainties. Second, there may be bequest motives at work. Third, in absence of health care insurance, large shocks to medical expenditures require some form of wealth to be liquid. Fourth, annuities may simply be too expensive, due to adverse selection effects or imperfect competition. Finally, as argued by Kotlikoff and Spivak (1981), pooling of longevity risks can be achieved within the family, essentially replicating an incomplete annuity market.

The analysis of Davidoff et al. (2005) convincingly shows that Yaari's result holds under more general assumptions for preferences and the economic environment, although full annuitization may no longer be optimal. Even for annuity-adverse scenario's, such as incomplete markets and bequest motives, the consumer should still annuitize a substantial fraction of his wealth. In contrast to most studies, d'Albis and Thibault (2012) instead finds that annuities are not optimal with maxmin preferences and uncertainty on the probability of survival. The evidence for bequest motives as an explanatory factor is mixed: Hayashi et al. (1996) do not find evidence in favor of the altruistic model underlying the bequest motive; Brown and Warshawsky (2001) and Hurd and Panis (2006) do not find an important role for bequest motives in the decision to annuitize either, while Bernheim (1991) and Laitner and Juster (1996) find evidence in favor of the altruistic model. Simulation studies by Videl-Meliá and Lejárrage-García (2006) and Lockwood (2012) do not find an important role for bequest motives in explaining the annuity puzzle. For health, Hurd and Panis (2006) find that individuals covered by medical insurance are less likely to cash out pension rights, as are those in better health, pointing to a possible precautionary savings motive for out-of-pocket medical expenditures. Finally, Mitchell et al. (1999) show that US market prices for annuities are not too high to prevent the rational agent from purchasing annuities, while Milevsky (1998) instead calculates that, as long as a person is not too risk averse and is willing to bear a small risk of out-living wealth, a female (male) has a 90% (85%) chance of beating the return on annuities until age 80, given the load factors prevailing in the Canadian insurance industry.

In practice, annuitization can take place via different channels. A typical social security system is a form of mandatory annuitization for most countries: during working life, the government taxes income, which is paid out during retirement until death. For defined benefit pension plans, a similar story holds, although in this case the employer and employee contribute to a pension fund, which pays out after retirement.[1] For defined contribution plans, a lump sum option is typically available, and, in the US case, is typically preferred to the annuitization option (Brown, 2001; Hurd and Panis, 2006). Butler and Teppa (2007) instead find a full annuitization rate of 72% using administrative data from Switzerland, and only 10% choosing the 100% lump sum. In total, it is fair to say that individuals are typically forced to annuitize a substantial part of their wealth due to pensions and social security. This holds specifically for the country studied in this paper, The Netherlands, where both social security and occupational pensions are paid out on an annuity basis (more details follow in Section 4.2). Voluntary annuitization in the non-pension annuity market may therefore be more appropriate to look at.

In this paper, we try to offer an alternative explanation for the observed low rate of annuitization, by analyzing the determinants of annuity ownership amongst non-retirees, as well as by analyzing possible misreporting in a household survey. The form of annuitization under study is arguably completely voluntary, in the sense that households can choose to allocate their wealth between cash holdings, buying annuities or private investments in financial markets (stocks, bonds) or real estate. As such, analyzing who purchases annuities and who do not can shed light on the annuity puzzle. Moreover, as noted by Hurd and Panis (2006) for the Health

[1] For the US, Brown and Warshawsky (2001) show an increase of DB plans offering a 100% lump sum option to 22% by 1997.

and Retirement Survey, respondents may report ownership with errors. In particular, when survey respondents underreport ownership of annuities, the annuity puzzle may not be as large as usually perceived. Opposite to Hurd and Panis (2006), our empirical model takes the measurement error problem into account, by allowing for classification errors in reported annuity ownership.

Exactly why ownership of annuities is misreported is not clear from the data, but several reasons can be mentioned. First, in many surveys of household finances, the questionnaires are lengthy and worded in jargon. Second, even if the respondents take the time and energy to fill out the questionnaire correctly, they may not understand the concept of annuities, and hence claim to own an annuity while in fact they have, say, a life insurance policy. Third, there may be a change in the household composition due to divorce, or due to a change in the financial respondent of the questionnaire, resulting in a wrong answer. Empirically, we cannot observe who is making the reporting errors and who are not, but in the estimation procedure, detailed in section 4.4, we can simultaneously estimate the parameters governing the determinants of ownership *and* the probability of misreporting, which may be either over- or underreporting.

We analyze joint ownership of two types of retirement saving products: annuities (i.e. a flow of money until death) and endowment policies (i.e. a lump sum payment), as these are likely to be substitutes. An endowment policy may be purchased to close the gap between intentions and actions with regard to retirement saving (Laibson et al., 1998), as the money is locked away safely, or to exploit the tax-preferred nature of the policies. As with annuities, ownership of an endowment policy may also be reported with error, for which we make a similar adjustment. Our estimation strategy thus covers misclassification errors in a bivariate setting, generalizing the model of Hausman et al. (1998), and the likelihood function for this model is derived in detail. We apply this model to a panel of Dutch households followed between 2000-2011.

We find a clear socio-economic gradient between owners and non-owners: the results indicate that age, income and wealth are important determinants for ownership of annuities and endowments. Moreover, the degree of underreporting annuity ownership is around 32%-points, which is a considerable fraction of the population. Around 12% is estimated to report to own an annuity while the household does not. On the contrary, we do not find evidence of over- or underreporting ownership of endowment policies. The results suggest that the annuity puzzle is not as large as usually perceived, and that older, richer and wealthier households are more likely to buy annuities.

The paper is structured in the following way. First, we briefly describe the Dutch pension system in Section 4.2. The data is discussed in Section 4.3, which contains descriptive evidence of classification errors. The empirical models are derived in Section 4.4 and the results are discussed in Section 4.5. Section 4.6 concludes.

4.2 Overview of the Dutch pension system

The Dutch pension system consists of three pillars.[2] The first pillar is the flat-rate state pension benefit, provided to all inhabitants aged 65 and above, which is the current retirement age. The only requirements for receiving social security are reaching the retirement age and living and/or working in The Netherlands; the accrual rate for each year lived in The Netherlands is 2%. In 2012, the gross monthly benefit amounted to €1085 for singles and €1513 for couples, paid out until death.

The second pillar, the occupational pensions, are mandatory for most employees, and both employers and employees contribute to a (usually defined benefit) pension fund. Traditionally, the Dutch occupational pension system is one of the most developed in the world, with pension funds holding around 125% of Dutch GDP in investments in 2008. Employees working for a given employer do not have freedom of choice in the decision to contribute to a pension fund, nor the decision which pension fund to contribute to; participation is mandatory and organized by the employer. The DB plans are converted into an annuity when reaching the retirement age, although there are some degrees of freedom to postpone claiming.

Recently, proposals have been made to reform the first and second pillars of the pension system due to ageing of the population as well as underfunding of pension funds during the crisis. These proposals encompass an increase in the statutory retirement age, from currently 65 to 67 in 2023. Furthermore, the occupational pen-

[2] See Bovenberg and Gradus (2008) for an overview of the Dutch pension system and its reforms.

sion system will shift from a defined benefit (DB) to a defined contribution (DC) system. For this paper, these future reforms are less important, although the uncertainty caused by the political debate as well as the financial crisis might have led to more purchases of annuity products. For an analysis of the (positive) effect of uncertainty on saving, see Van Santen (2012).

The third pillar of the pension system concerns private pension savings, such as annuities bought from banks or insurance companies or private retirement saving accounts. The annuities and endowments policies studied in this paper fall in this third pillar. The third pillar is less popular in the Netherlands, as documented by Mastrogiacomo and Alessie (2011). In our empirical analysis, we control for wealth holdings in other forms, such as housing, stocks, bonds and bank accounts.

4.3 Data

For the empirical analysis, we use the DNB Household Survey (DHS). This annual household survey is administered by CentERData, Tilburg, The Netherlands, and invites all adult members of a household to participate, following them over time. The respondents represent the Dutch population aged 16 and above. The DHS is administered via the internet, and internet access is provided to those that do not have access themselves. The DHS has been running since 1993, and the data from 2011 are the most recent available. The DHS collects information on many socio-economic characteristics of the household and its members, including a detailed breakdown of household income and wealth holdings, which can be used to construct measures of total assets, financial assets and housing assets; see Alessie et al. (2002) for an extended description. We use the DHS data from 2000 onwards.

The questions on assets and liabilities are of special interest for this study. This questionnaire is answered by all adult members of the household, and subsequently aggregated to the household level. The so-called "financial respondent" answers the questions for joint household assets and liabilities. The DHS asks respondents to indicate whether or not they own an annuity, and if they do, the value of the annuity. The exact wording of the question is as follows:

Question 4.1. *Did you, in or before year T, take out SINGLE-PREMIUM INSURANCE* *and/or ANNUITY INSURANCE (pension insurance), which was still in effect on 31 December T? Do not include annuity insurance that you have taken out by using money from your employer-sponsored savings plan, nor include pension arrangements provided by your employer or professional pension plans here.*

The survey software allows the respondents to see (via a hyperlink) the following definitions of the single-premium insurance and the annuity insurance referred to in question 4.1:

Definition 4.1. *By taking out annuity insurance the insured is entitled to periodic payments, the so-called annuity. The ANNUITY is paid out periodically (for example annually) as of a certain date until the time of death of the insured. PENSION INSURANCE is a specific type of annuity insurance. SINGLE-PREMIUM INSURANCE is also a specific type of annuity insurance, which involves (as the name indicates) a one-time premium. Other types of annuity insurance involve periodical (for example annual) premium payments. Under certain conditions, these premium payments are income tax deductible.*

The question for endowment policies is worded as follows:

Question 4.2. *Did you, on 31 December year T, have one or more ENDOWMENT INSURANCE POLICIES that were still in effect? Do not include life-insurance policies connected to an (improved) traditional life-insurance mortgage here. These will be reported later.*

Respondents can see the following definition of the endowment policy:

Definition 4.2. *ENDOWMENT INSURANCE is a kind of life-insurance that pays out a lump sum (so, this is not an annuity) to the insured at the maturity of the insurance (or, in some cases, at the time of death of the insured, whichever comes first). The premium payments cannot be deducted from the taxable income, but the lump sum payment is under certain conditions tax free. The life-insurance which is connected to an improved traditional life-insurance mortgage is an example of an endowment insurance. With certain kinds of endowment insurance policies, the insured can decide upon the way his premium payments will be invested (for example in deposits, shares, or bonds).*

The assets and liabilities questionnaire further asks details (i.e. ownership and amounts) on around 40 other asset and liability categories, such as bank accounts, credit cards, vehicles and risky assets. These allow the construction of financial wealth (liquid assets and liabilities, stocks and bonds) as well as net worth (financial wealth, durable goods, housing wealth minus any debts on them) as control variables.

The dependent variables in our analysis thus consist of ownership of annuities and endowment policies; both are a binary variable. As explanatory variables we take Age and its square, Education (benchmark lowest educated), Marital status (benchmark single), Log of (Number of children+1), Home ownership (benchmark tenants), Health status and Time fixed effects. Employment characteristics are captured by the variables No permanent contract, self-employed (benchmark employees with permanent contract) and Civil servant. Moreover, we control for the level of net worth (financial wealth, housing wealth, durable goods minus loans, mortgage etc.) of the household, to which we apply an inverse hyperbolic sine transformation to minimize the impact of outliers. Finally, we control for the natural logarithm of (real) household income. Table 4.1 shows the descriptive statistics of all variables used. The sample consists of 7089 observations in 2065 households, and is selected to include those aged 25-64, and to be active on the labor market, either working (93%) or unemployed (7%). (Early) retirees are not included in the sample.

Table 4.1. Summary statistics

Variable	Mean	Median	St. dev.
Ownership annuities	0.32	0.00	0.47
Ownership endowments	0.17	0.00	0.38
Value annuities	5012.45	0.00	21404.92
Value endowments	3933.82	0.00	18452.85
Value annuities | Ownership	15841.85	4014.561	35733.12
Value endowments | Ownership	22709.16	10314.27	39246.51
Financial wealth	37144.50	13911.75	89434.31
Net wealth	6.73×10^7	108699.93	5.64×10^9
Real income	31584.72	27705.67	20036.64
Age	44.99	46.00	10.14
Low secondary educated	0.25	0.00	0.43
High secondary educated	0.31	0.00	0.46
Vocational educated	0.29	0.00	0.45
University educated	0.15	0.00	0.36
Home owner	0.68	1.00	0.47
Partner	0.65	1.00	0.48
Number of children	0.87	0.00	1.14
No permanent contract	0.07	0.00	0.25
Self employed	0.05	0.00	0.21
Civil servant	0.18	0.00	0.39
Good health	0.87	1.00	0.33
Disabled	0.18	0.00	0.38

Note: N=7089. All values in real 2006 Euros.

Table 4.1 shows an ownership rate of 32% for annuities, and 17% for endowment policies. Conditional on ownership, the values of the annuity and endowment policy are typically low. Analyzing the values is left for further research. Especially net worth and, to a lesser extent, real income and number of children, are skewed, hence we apply the transformations alluded to.

4.3.1 Misclassification: descriptive evidence

We analyze the determinants of the binary variables "Annuities" and "Endowments". Here, we give some descriptive evidence of why we should consider misclassification in these variables. Table 4.2 shows, for Annuities in panel A and for Endowments in Panel B, why misclassification may be important. In panel A (B), on the left side, we compare ownership of annuities (endowments) with the corresponding value of annuities (endowments) asked in a follow-up question. For 2.6% (4.6%), we find that the value of annuities (endowments) is either zero, or the respondents do not give any value of the annuities (endowments). On the right side, we compare ownership in year $t-1$ with ownership in year t. Due to the very nature of both annuities and endowments, it is unlikely that the household sells the product, as there basically is no secondary market for annuities. Moreover, terminating the contract is typically subject to a fine, which has to be paid to the issuing party. As such, once the household buys the annuity or endowment policy, it is likely to keep the product until it starts paying out, which typically occurs at retirement. We see in Table 4.2 that 3.0% of the respondents appear to have "sold" their annuity, and 2.5% have "sold" their endowment policy. Most likely, these are reporting errors. Of course, there may be other forms of misclassification in ownership, such as, confusions with life insurances or other insurance products, or recall bias. To estimate the degree of misclassification, we use an empirical model explained in Section 4.4 below.

Table 4.2. Sources of potential misclassification

Panel A: Annuities

	Value of annuities		Lagged ownership	
	Zero/missing	Positive	No annuities $t-1$	Annuities $t-1$
No annuities	68.36	0.00	64.59	3.03
Annuities	2.61	29.03	2.95	29.44

Panel B: Endowments

	Value of endowments		Lagged ownership	
	Zero/missing	Positive	No endowments $t-1$	Endowments $t-1$
No endowments	82.68	0.00	80.28	2.51
Endowments	4.63	12.70	1.84	15.37

Entries are percentages of cross-tabulation of ownership and an indicator whether or not the value of the annuity/endowment is zero or missing ($N = 7089$), as well as cross-tabulation with lagged ownership of annuities/endowments ($N = 5055$)

4.4 Models

4.4.1 Pooled, univariate model

This section draws upon Hausman et al. (1998).[3] Let y_{it} denote the observed (dichotomous) ownership of annuity products for household i in year t. In particular, $y_{it} = 1$ if the household owns an annuity, and $y_{it} = 0$ if it does not.[4] We can write the probability of owning an annuity, as a function of a vector of household characteristics $\boldsymbol{x}_{it}$, as a probit model:

$$\mathbb{P}\left(y_{it} = 1 | \boldsymbol{x}_{it}, \boldsymbol{\beta}\right) = \Phi\left(\boldsymbol{x}'_{it}\boldsymbol{\beta}\right) \tag{4.1}$$

As explained in the previous section, for various reasons, ownership is likely to be coded with error. Denote the (unobserved) true value of ownership by $\tilde{y}_{it}$, not to be confused with the underlying latent variable sometimes denoted similarly. Then, the probit model allowing for misclassification is derived as follows, where we suppress the household and time indexes and the dependence on $\boldsymbol{x}$ for notational convenience:

$$\begin{aligned}\mathbb{P}(y=1) &= \mathbb{P}(y=1|\tilde{y}=1)\cdot\mathbb{P}(\tilde{y}=1) + \mathbb{P}(y=1|\tilde{y}=0)\cdot\mathbb{P}(\tilde{y}=0)\\ &= \left[1-\mathbb{P}(y=0|\tilde{y}=1)\right]\mathbb{P}(\tilde{y}=1) + \mathbb{P}(y=1|\tilde{y}=0)\cdot\left[1-\mathbb{P}(\tilde{y}=1)\right]\end{aligned} \tag{4.2}$$

We make the following definitions on the misclassification probabilities:

$$\alpha_0 = \mathbb{P}(y=1|\tilde{y}=0) : \text{Wrongly classified as owner} \tag{4.3a}$$

$$\alpha_1 = \mathbb{P}(y=0|\tilde{y}=1) : \text{Wrongly classified as non-owner} \tag{4.3b}$$

Then we can write the above expression (4.2) as

$$\mathbb{P}(y=1) = \left[1-\alpha_1\right]\mathbb{P}(\tilde{y}=1) + \alpha_0\left[1-\mathbb{P}(\tilde{y}=1)\right]$$

[3] For an ordered response model with misclassification errors, see Dustmann and van Soest (2004).

[4] A similar indicator can be used for the ownership of an endowment policy. To ease notation, we will introduce the distinction in section 4.4.2 analyzing annuities and endowments jointly.

$$= [1 - \alpha_0 - \alpha_1] \, \mathbb{P}(\tilde{y} = 1) + \alpha_0 \tag{4.4}$$

The density function of the outcome variable, which follows the Bernoulli distribution, is written as

$$f(y_{it}|\boldsymbol{x}_{it}, \boldsymbol{\beta}) = \left((1 - \alpha_0 - \alpha_1) \, \Phi \left(\boldsymbol{x}_{it}' \boldsymbol{\beta}\right) + \alpha_0\right)^{y_{it}} \left(1 - \alpha_0 - (1 - \alpha_0 - \alpha_1) \, \Phi \left(\boldsymbol{x}_{it}' \boldsymbol{\beta}\right)\right)^{1 - y_{it}}$$

Taking the log gives the sample likelihood for the pooled probit model with misclassification:

$$\begin{aligned} \ln L \left(\boldsymbol{\beta}, \alpha_0, \alpha_1\right) = & \sum_{i=1}^{n} \sum_{t=1}^{T} y_{it} \ln \left((1 - \alpha_0 - \alpha_1) \, \Phi \left(\boldsymbol{x}_{it}' \boldsymbol{\beta}\right) + \alpha_0\right) \\ & + (1 - y_{it}) \ln \left(1 - \alpha_0 - (1 - \alpha_0 - \alpha_1) \, \Phi \left(\boldsymbol{x}_{it}' \boldsymbol{\beta}\right)\right) \end{aligned}$$

Identification of this model is discussed in Hausman et al. (1998), who show that due to the functional form of the probit model, one can identify α_0 and α_1 under the condition that $\alpha_0 + \alpha_1 < 1$.[5] Hausman et al. (1998) also introduce a semi-parametric estimator to avoid the normality assumption and still identify the misclassification parameters, but the results, when applied to the Panel Study of Income Dynamics analyzing job changes, are rather similar. A semi-parametric analysis of annuity and endowment policy ownership is left for future work.

The model presented above can be extended in several ways. First, one can make the misclassification parameters conditional on observed characteristics, i.e. we model $\alpha_0 = \alpha_0 \left(\boldsymbol{z}_{it}\right)$ for a vector of explanatory variables $\boldsymbol{z}_{it}$. Second, we can exploit the panel feature of the data, by introducing (random) household effects. Both extensions are beyond the scope of this paper, although we do use panel-robust standard errors.[6] Instead, we introduce a system of equations in section

[5] In constructing the likelihood, we use a logit transformation of the probabilities, and estimate the parameters γ_0 and γ_1 in $\alpha_j = \frac{\exp[\gamma_j]}{1+\exp[\gamma_0]+\exp[\gamma_1]}$, $j = 0, 1$. This ensures the identifiying condition is fulfilled, and that both probabilities are between zero and one. The Delta method is used to construct confidence intervals for α_0 and α_1.

[6] Dustmann and van Soest (2001) introduce a panel data ordered response model with misclassified language fluency indicators.

4.4.2 below to analyze ownership of annuities and endowments policies jointly.

4.4.2 Bivariate model

The bivariate model can be described as follows. Let y_1^* and y_2^* be two latent variables modeled as

$$y_1^* = \boldsymbol{x}_1'\boldsymbol{\beta}_1 + u_1 \tag{4.5a}$$

$$y_2^* = \boldsymbol{x}_2'\boldsymbol{\beta}_2 + u_2 \tag{4.5b}$$

where $\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$. The observation rule is as follows:

$$y_1 = \mathbb{1}(y_1^* > 0) \tag{4.6a}$$

$$y_2 = \mathbb{1}(y_2^* > 0) \tag{4.6b}$$

with $\mathbb{1}(A) = 1$ if event A occurs and zero otherwise. In the bivariate model with misclassification, without making any assumptions on the misclassification probabilities, there are 12 possible classification errors. These arise from either y_1 or y_2 or both being misclassified. Hence, for each pair of "true values", there are 3 misclassification probabilities. The probabilities and notation used are given in table 4.3 below.

To reduce the number of additional parameters to be estimated, we can make an independence assumption: the probability of misclassifying y_1 is independent of the probability of misclassifying y_2. This assumption is not innocuous, as there may well be reasons for dependence between the probabilities. For example, those misclassifying annuity ownership might also misclassify ownership of endowment policies, both due to a lack of financial literacy or unobserved heterogeneity. Similarly, the respondent may confuse an annuity with an endowment policy, imposing a correlation between the misclassification probabilities. Still, under independence, there are just 4 additional parameters to be estimated: α_0^k and α_1^k, for $k = 1, 2$, defined as in (4.3a) and (4.3b). Multiplying these 4 probabilities exhausts all possible

Table 4.3. Bivariate misclassification probabilities

Number of Errors	Misclassification probability	Notation under Independence
2	$\mathbb{P}(y_1 = 0, y_2 = 0 \| \tilde{y}_1 = 1, \tilde{y}_2 = 1)$	$\alpha_1^1 \cdot \alpha_1^2$
1	$\mathbb{P}(y_1 = 0, y_2 = 1 \| \tilde{y}_1 = 1, \tilde{y}_2 = 1)$	$\alpha_1^1 \cdot (1 - \alpha_1^2)$
1	$\mathbb{P}(y_1 = 1, y_2 = 0 \| \tilde{y}_1 = 1, \tilde{y}_2 = 1)$	$(1 - \alpha_1^1) \cdot \alpha_1^2$
0	$\mathbb{P}(y_1 = 1, y_2 = 1 \| \tilde{y}_1 = 1, \tilde{y}_2 = 1)$	$(1 - \alpha_1^1) \cdot (1 - \alpha_1^2)$
2	$\mathbb{P}(y_1 = 0, y_2 = 1 \| \tilde{y}_1 = 1, \tilde{y}_2 = 0)$	$\alpha_1^1 \cdot \alpha_0^2$
1	$\mathbb{P}(y_1 = 1, y_2 = 1 \| \tilde{y}_1 = 1, \tilde{y}_2 = 0)$	$(1 - \alpha_1^1) \cdot \alpha_0^2$
1	$\mathbb{P}(y_1 = 0, y_2 = 0 \| \tilde{y}_1 = 1, \tilde{y}_2 = 0)$	$\alpha_1^1 \cdot (1 - \alpha_0^2)$
0	$\mathbb{P}(y_1 = 1, y_2 = 0 \| \tilde{y}_1 = 1, \tilde{y}_2 = 0)$	$(1 - \alpha_1^1) \cdot (1 - \alpha_0^2)$
2	$\mathbb{P}(y_1 = 1, y_2 = 0 \| \tilde{y}_1 = 0, \tilde{y}_2 = 1)$	$\alpha_0^1 \cdot \alpha_1^2$
1	$\mathbb{P}(y_1 = 1, y_2 = 1 \| \tilde{y}_1 = 0, \tilde{y}_2 = 1)$	$\alpha_0^1 \cdot (1 - \alpha_1^2)$
1	$\mathbb{P}(y_1 = 0, y_2 = 0 \| \tilde{y}_1 = 0, \tilde{y}_2 = 1)$	$(1 - \alpha_0^1) \cdot \alpha_1^2$
0	$\mathbb{P}(y_1 = 0, y_2 = 1 \| \tilde{y}_1 = 0, \tilde{y}_2 = 1)$	$(1 - \alpha_0^1) \cdot (1 - \alpha_1^2)$
2	$\mathbb{P}(y_1 = 1, y_2 = 1 \| \tilde{y}_1 = 0, \tilde{y}_2 = 0)$	$\alpha_0^1 \cdot \alpha_0^2$
1	$\mathbb{P}(y_1 = 1, y_2 = 0 \| \tilde{y}_1 = 0, \tilde{y}_2 = 0)$	$\alpha_0^1 \cdot (1 - \alpha_0^2)$
1	$\mathbb{P}(y_1 = 0, y_2 = 1 \| \tilde{y}_1 = 0, \tilde{y}_2 = 0)$	$(1 - \alpha_0^1) \cdot \alpha_0^2$
0	$\mathbb{P}(y_1 = 0, y_2 = 0 \| \tilde{y}_1 = 0, \tilde{y}_2 = 0)$	$(1 - \alpha_0^1) \cdot (1 - \alpha_0^2)$

misclassification possibilities, as shown in table 4.3.[7]

[7] Without the assumption of independence, the likelihood function did not converge for the dataset at hand.

Likelihood contributions

We assume that the probabilities for the true values follow a bivariate probit model:

$$\begin{aligned}
\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) &= \Phi_2(\boldsymbol{x}_1'\boldsymbol{\beta}_1, \boldsymbol{x}_2'\boldsymbol{\beta}_2, \rho) \\
\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) &= \Phi_2(\boldsymbol{x}_1'\boldsymbol{\beta}_1, -\boldsymbol{x}_2'\boldsymbol{\beta}_2, -\rho) \\
\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) &= \Phi_2(-\boldsymbol{x}_1'\boldsymbol{\beta}_1, \boldsymbol{x}_2'\boldsymbol{\beta}_2, -\rho)
\end{aligned}$$

Here, y_1 denotes Annuity ownership, y_2 denotes Endowment policy ownership, $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$ denote the vectors of (possibly different) explanatory variables in the two equations,[8] $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are parameters to be estimated, and ρ is the correlation between the error terms (see equations 4.5a and 4.5b). Φ_2 denotes the bivariate normal CDF and, as before, a tilde indicates a true value.

The probability of observing $y_1 = 1, y_2 = 1$ can be obtained by summing four different probabilities, namely, of (correctly) observing $y_1 = 1, y_2 = 1$ and of (incorrectly) observing $y_1 = 1, y_2 = 1$ while in fact the household does not own annuities or endowments, or both. We assume independence between misclassifying either binary variable, and use the notation from Table 4.3 to arrive at the following probability of this event:

$$\begin{aligned}
\mathbb{P}(y_1 = 1, y_2 = 1) = {} & \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) \\
& + \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 0\right) \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 0) \\
& + \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 0\right) \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
& + \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 1\right) \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
& = [1 - \mathbb{P}\left(y_1 = 0, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \\
& - \mathbb{P}\left(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \\
& - \mathbb{P}\left(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right)] \, \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1)
\end{aligned}$$

[8] Note that, unlike a linear (SUR) model, even when $\boldsymbol{x}_1 = \boldsymbol{x}_2$, the system estimator for probit regressions is more efficient.

$$
\begin{aligned}
&+ \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 0\right) \left[1 - \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1)\right. \\
&- \left. \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) - \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0)\right] \\
&+ \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 0\right) \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&+ \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 1\right) \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
&= \left[1 - \alpha_1^1\alpha_1^2 - \alpha_1^1(1 - \alpha_1^2) - (1 - \alpha_1^1)\alpha_1^2\right] \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) \\
&+ \alpha_0^1\alpha_0^2 \left[1 - \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) - \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) - \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0)\right] \\
&+ (1 - \alpha_1^1)\alpha_0^2\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) + \alpha_0^1(1 - \alpha_1^2)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
&= \left[(1 - \alpha_1^1)(1 - \alpha_1^2) - \alpha_0^1\alpha_0^2\right] \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) + \alpha_0^1\alpha_0^2 \\
&+ \alpha_0^2(1 - \alpha_0^1 - \alpha_1^1)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) + \alpha_0^1(1 - \alpha_0^2 - \alpha_1^2)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1)
\end{aligned}
$$

The remaining probabilities, $\mathbb{P}(y_1 = 1, y_2 = 0)$ and $\mathbb{P}(y_1 = 0, y_2 = 1)$ are determined in a similar fashion, and are given in the appendix. With these probabilities in hand, we can write down the log-likelihood function for the pooled bivariate probit model with misclassification, where y_{jk} denotes the indicator for observing $y_1 = j$ and $y_{2=k}$, $j, k = 0, 1$:

$$
\begin{aligned}
\ln L = &\sum_{i=1}^{N} \ln \mathbb{P}(y_1 = 1, y_2 = 1) + y_{10} \ln \mathbb{P}(y_1 = 1, y_2 = 0) + y_{01} \ln \mathbb{P}(y_1 = 0, y_2 = 1) \\
&+ (1 - y_{11} - y_{10} - y_{01}) \ln\left(1 - \mathbb{P}(y_1 = 1, y_2 = 1) - \mathbb{P}(y_1 = 1, y_2 = 0)\right. \\
&\left.- \mathbb{P}(y_1 = 0, y_2 = 1)\right)
\end{aligned}
$$

Identification is again on functional form. A panel data model with (correlated) random household effects is feasible, but numerically challenging, and left for future research. Moreover, as Wooldridge (2010) argues, a pooled model has the additional robustness advantage against misspecification of the joint density, i.e. we use a partial likelihood approach. The log-likelihood is optimized[9] using the Mata matrix language of Stata 10.1, based on analytical gradients and the BHHH routine (Berndt et al., 1974).

[9] We use (re-scaled) logit transformations of the misclassification parameters and the correlation parameter ρ to ensure the probabilities (correlation) are between zero (minus one) and one.

4.5 Results

4.5.1 Univariate probit models

We start the discussion of the results with a simple, univariate probit model without misclassification, as a benchmark to compare the remaining results against. In table 4.4, we present parameter estimates and marginal effects, evaluated at the means of the explanatory variables (see table 4.1). For the transformed variables net wealth, real income and the number of children, we present the marginal effect for the mean individual of the untransformed variable. Standard errors are based on a panel-robust estimate of the covariance matrix, allowing for within-household correlations over time and arbitrary forms of heteroscedasticity. All regressions include a full set of time fixed effects.

We find an upward sloping age path for both endowments and annuities, with the probability of owning an annuity increasing by 0.3%-point at each age; for endowments the marginal effect is not significantly different from zero. We observe a clear socio-economic gradient: higher-educated and higher-income households are more likely to own annuities, and wealthier and higher-income households are more likely to own endowment policies. The marginal effects of income and wealth are small however; an extra 100,000 euro in wealth results in a 0.0066% higher probability of owning an endowment policy, while an extra 1,000 euro annual income increases the probability of owning an annuity by 3.9%. Home owners are more likely to own annuities and endowment policies; for endowment policies, this might actually point towards misclassification errors, as mortgages providers typically require the household to purchase a life insurance policy.[10] The employment indicators are insignificant, except for being a civil servant, which are 6.5% less likely to own annuities compared to wage workers, which may be due to a less risky wage profile.[11] We don't find big effects of health, except for being disabled

[10] When allowing the misclassification parameters to depend on home ownership (not reported), we find that homeowners are more likely to underreport annuity ownership, but no significant differences for overreporting annuity ownership. The misclassification probabilities for endowment policies do not depend on home ownership.

[11] In results not reported here, we have added an indicator variable for being enrolled in an occupational pension fund, as well as its interaction with the indicators No permanent contract and Self employed. We find that the pension fund dummy has a significant positive effect on endowment policies; the in-

Table 4.4. Univariate probit estimates and marginal effects

	Annuities		Endowments	
	Probit estimates	Marginal effects	Probit estimates	Marginal effects
Age	0.0850***	0.0031**	0.0827**	-0.0012
	(0.0296)	(0.0013)	(0.0336)	(0.0011)
Age^2 /100	-0.0851**		-0.0968**	
	(0.0333)		(0.0380)	
IH (Net wealth)[a]	0.00367	2.99×10^{-11}	0.0112**	6.62×10^{-11}*
	(0.00432)	(3.57×10^{-11})	(0.00540)	(3.53×10^{-11})
Log (real income)[a]	0.339***	3.92×10^{-6}***	0.233***	1.95×10^{-6}***
	(0.0586)	(0.69×10^{-6})	(0.0661)	(0.56×10^{-6})
High secondary educated	0.164*	0.0608*	0.136	0.0368
	(0.0930)	(0.0347)	(0.107)	(0.0297)
Vocational educated	0.280***	0.105***	0.143	0.0389
	(0.0971)	(0.0369)	(0.109)	(0.0304)
University educated	0.266**	0.100**	0.0823	0.0223
	(0.113)	(0.0437)	(0.132)	(0.0368)
Home owner	0.167**	0.0603**	0.463***	0.113***
	(0.0833)	(0.0295)	(0.101)	(0.0224)
Partner	0.153*	0.0552*	0.118	0.0307
	(0.0827)	(0.0298)	(0.0940)	(0.0242)
Log (nr children+1)[a]	-0.115*	-0.0485	-0.0316	-0.0097
	(0.0692)	(0.0304)	(0.0768)	(0.0240)
No permanent contract	0.0451	0.0166	-0.0111	-0.0029
	(0.0976)	(0.0363)	(0.102)	(0.0267)
Self employed	-0.186	-0.0654	-0.0888	-0.0226
	(0.128)	(0.0433)	(0.129)	(0.0319)
Civil servant	-0.183**	-0.0650**	-0.0643	-0.0167
	(0.0858)	(0.0297)	(0.0998)	(0.0254)
Good health	0.0681	0.0246	0.0176	0.0046
	(0.0594)	(0.0213)	(0.0649)	(0.0170)
Disabled	-0.0351	-0.0128	0.160**	0.0442**
	(0.0719)	(0.0261)	(0.0777)	(0.0223)
Constant	-6.454***		-5.714***	
	(0.805)		(0.866)	
Observations	7089		7089	
Households	2065		2065	
Pseudo-R^2	0.0467		0.0558	
log L	-4218.022		-3085.397	
p-value model	0.000		0.000	
p-value education	0.0247		0.536	
p-value time effects	0.0157		0.0633	
Mean dep. var.	0.316		0.173	

Panel-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Time effects included, not reported. Marginal effects calculated for mean individual
[a] Marginal effects calculated for untransformed net wealth, real income and number of children

(self-reported), which increases the probability of owning a endowment policy.

Table 4.5 shows the result of the univariate probit model allowing for misclassified ownership indicators. The coefficients of the explanatory variables in the annuity ownership equation remain similar in sign, and significance, although the magnitude increases in absolute value, as expected.[12] In particular, the slope of the annuities-age profile now becomes more hump-shaped, and the socio-economic gradient becomes even sharper. Home ownership is no longer significant, as is the civil servant dummy.

The misclassification parameters for annuities are significantly different from zero at the conventional 5% level, and are remarkably high. We estimate an over-reporting of annuity ownership by 12%-points, and under-reporting of 36.3%-points. As such, misclassification of annuity ownership in a socio-economic survey can resolve part of the annuity puzzle: a substantial fraction of the population is estimated to own annuities, while they report not to own annuities. The reported probability of owning annuities was 32% (see table 4.1), while we estimate this probability to be 56.3%. On the contrary, for endowment policies, we do not find any evidence of misreporting ownership; the sample likelihood is highest by setting both misclassification parameters equal to zero. Therefore, the reported parameters are identical to those presented in table 4.4.

teraction terms are negative but jointly insignificant. For annuities, the pension fund dummy is positive but insignificant; the interaction terms are negative and not significant. Hence, we do not find evidence in favor of hedging against a risky income profile.

[12] Note that $E(y|\boldsymbol{x}) = \alpha_0 + (1 - \alpha_0 - \alpha_1)\Phi(\boldsymbol{x}'\boldsymbol{\beta})$, and hence the estimated $\boldsymbol{\beta}$ parameters are scaled upward.

Table 4.5. Univariate probit estimates with misclassification

	Annuities		Endowments	
	Estimates	Marginal effects	Estimates	Marginal effects
Age	0.183**	0.0074	0.0827**	-0.0012
	(0.0779)	(1.982)	(0.0336)	(0.0011)
$Age^2/100$	-0.183**		-0.0968**	
	(0.0837)		(0.0380)	
IH(Net wealth)[a]	0.0049	4.27×10^{-11}	0.0112**	6.62×10^{-11}*
	(0.0092)	(8.13×10^{-11})	(0.0054)	(3.53×10^{-11})
Log (real income)[a]	0.750**	9.29×10^{-6}**	0.233***	1.95×10^{-6}***
	(0.3055)	(4.21×10^{-6})	(0.0661)	(0.56×10^{-6})
High secondary educated	0.357	0.140	0.136	0.0368
	(0.243)	(0.0957)	(0.107)	(0.0297)
Vocational educated	0.612*	0.240*	0.143	0.0389
	(0.332)	(0.129)	(0.109)	(0.0304)
University educated	0.580*	0.228*	0.0823	0.0223
	(0.322)	(0.123)	(0.132)	(0.0368)
Home owner	0.313	0.120	0.463***	0.113***
	(0.200)	(0.0811)	(0.101)	(0.0224)
Partner	0.312	0.120	0.118	0.0307
	(0.195)	(0.0743)	(0.0940)	(0.0242)
Log (nr children +1)[a]	-0.233	-0.105	-0.0317	-0.0097
	(0.147)	(0.0709)	(0.0767)	(0.0240)
No permanent contract	0.123	0.0484	-0.0110	-0.0029
	(0.206)	(0.0814)	(0.102)	(0.0267)
Self employed	-0.402	-0.148	-0.0888	-0.0226
	(0.313)	(0.115)	(0.129)	(0.0319)
Civil servant	-0.424	-0.159	-0.0643	-0.0167
	(0.266)	(0.0992)	(0.0998)	(0.0254)
Good health	0.127	0.0490	0.0177	0.0046
	(0.142)	(0.0539)	(0.0649)	(0.0170)
Disabled	-0.0946	-0.0367	0.160**	0.0442**
	(0.166)	(0.0653)	(0.0777)	(0.0223)
Constant	-13.46***		-5.714***	
	(4.389)		(0.8656)	
α_0	0.120***		0.000	
	(0.0413)		(0.000)	
α_1	0.363***		0.000	
	(0.155)		(0.000)	
Observations	7089		7089	
Households	2065		2065	
Pseudo-R^2	0.0476		0.0558	
$\log L$	-4213.896		-3085.397	
p-value α_0,α_1	0.003		1.000	
p-value model	0.000		0.000	
p-value education	0.288		0.536	
p-value time effects	0.829		0.063	

Panel-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Time effects included, not reported. Marginal effects calculated for mean individual
α_0: Wrongly classified as $y = 1$; α_1: Wrongly classified as $y = 0$
[a] Marginal effects calculated for untransformed net wealth, real income and number of children

4.5.2 Bivariate probit models

In the bivariate case, we estimate $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ jointly with the correlation parameter ρ. The first two columns of table 4.6 shows the parameter estimates for the bivariate probit model ignoring potential misclassification errors. We observe that the errors are correlated, and the estimated correlation coefficient equals 0.216. This positive correlation points towards annuities and endowment policies being complements, rather than substitutes: those owning an annuity are more likely to own an endowment policy. However, it may well be that ownership of both products is concentrated in the highest socio-economic classes of the Dutch population, who simply have more wealth to allocate to retirement products. Furthermore, this group has most to gain of the tax-preferred nature of these products; in fact in tax avoidance terms, the products are complements. The estimated coefficients are very similar to those obtained in table 4.4 above, as was to be expected. The efficiency gain of estimating both equations jointly is small, given the incremental decrease in the standard errors compared to table 4.4.

In the bivariate probit model with misclassification, presented in the last two columns of table 4.6, we observe that the probabilities of misclassification are again zero for endowment policies, and smaller and less significant for annuities, although the probability of under-reporting is still significantly different from zero at the 10% level. The estimated error correlation is somewhat higher at 0.364. The remaining coefficients still point towards the socio-economic gradient in ownership of both annuities and endowment policies.

Table 4.6. Bivariate probit estimates

	No misclassification		With misclassification	
	Annuities	Endowments	Annuities	Endowments
Age	0.0860***	0.0842**	0.154*	0.0843**
	(0.0296)	(0.0334)	(0.0886)	(0.0335)
Age^2 /100	-0.0862***	-0.0987***	-0.155*	-0.0988***
	(0.0333)	(0.0378)	(0.0937)	(0.0378)
IH (net wealth)	0.00378	0.0118**	0.00496	0.0118**
	(0.00432)	(0.00530)	(0.00754)	(0.00531)
Log (real income)	0.339***	0.236***	0.620**	0.236***
	(0.0585)	(0.0656)	(0.300)	(0.0658)
High secondary educated	0.163*	0.133	0.263	0.133
	(0.0930)	(0.107)	(0.190)	(0.108)
Vocational educated	0.280***	0.144	0.471*	0.144
	(0.0970)	(0.108)	(0.242)	(0.108)
University educated	0.265**	0.0833	0.457*	0.0844
	(0.113)	(0.132)	(0.261)	(0.132)
Home owner	0.167**	0.464***	0.282	0.462***
	(0.0832)	(0.101)	(0.182)	(0.101)
Partner	0.153*	0.114	0.246	0.115
	(0.0825)	(0.0937)	(0.164)	(0.0937)
Log (nr children+1)	-0.117*	-0.0348	-0.208	-0.0344
	(0.0692)	(0.0765)	(0.148)	(0.0766)
No permanent contract	0.0449	-0.0207	0.0952	-0.0181
	(0.0977)	(0.101)	(0.178)	(0.101)
Self employed	-0.186	-0.0918	-0.336	-0.0919
	(0.129)	(0.129)	(0.279)	(0.129)
Civil servant	-0.182**	-0.0651	-0.358	-0.0651
	(0.0858)	(0.0995)	(0.288)	(0.0996)
Good health	0.0673	0.0156	0.0966	0.0160
	(0.0594)	(0.0648)	(0.114)	(0.0648)
Disabled	-0.0348	0.160**	-0.0735	0.160**
	(0.0721)	(0.0778)	(0.132)	(0.0777)
Constant	-6.482***	-5.778***	-11.14**	-5.777***
	(0.806)	(0.860)	(4.873)	(0.863)
ρ (Error correlation)	0.216***	0.216***	0.364*	0.364*
	(0.0446)	(0.0446)	(0.220)	(0.220)
α_0^1			0.0913	
			(0.0617)	
α_0^2				0.000
				(0.000)
α_1^1			0.320*	
			(0.188)	
α_1^2				0.000
				(0.000)
Observations	7089	7089	7089	7089
Households	2065	2065	2065	2065
log L	-7259.436	-7259.436	-7257.727	-7257.727
Pseudo-R^2	0.0470	0.0470	0.0473	0.0473
p-value model	0.000	0.000	0.000	0.000
p-value education	0.0244	0.544	0.261	0.543
p-value time effects	0.0147	0.0592	0.437	0.0599
p-value α_0^1, α_0^2, α_1^1, α_1^2			0.064	0.064

Panel-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Time effects included, not reported

4.6 Conclusion

In this paper we have investigated the 'Annuity puzzle', stating that only a fraction of households annuitize their wealth, despite the theoretical attractiveness of annuities as a hedge against lifespan uncertainty. Our empirical model accounts for misclassification errors of owning annuities and endowment policies in a socio-economic survey, which may be due to changes in household composition over time, confusion with similar products such as pension insurance or mortgage-related life insurance policies, recall bias or other reasons. Using a panel of Dutch households, we find that annuities are most likely to be misclassified, in a direction that can help to understand the annuity puzzle. 36% of the sample is estimated to own an annuity, but have reported not to own annuities; 12% is estimated not to own an annuity while they report to own an annuity. As such, the sample proportion of households owning an annuity increases from 32% to 56%. If our specification is correct, part of the annuity puzzle can simply be explained by measurement errors. On the contrary, we do not find any evidence of misreporting ownership of endowment policies, which pay out a lump sum on maturity, and are therefore not hedging against lifespan uncertainty.

The determinants of ownership of both annuities and endowment policies identify a socio-economic gradient, with the higher-educated, higher-income and wealthier households more likely to own either product. Moreover, ownership of annuities is positively correlated with ownership of endowments, which could reveal that ownership is indeed concentrated in the highest socio-economic class of the population. If government policy is to be designed to stimulate the ownership of annuities, in order to prevent individuals from out-running their wealth during retirement, policy should be aimed at the less affluent subset of the population. It is likely that financial literacy is low amongst non-owners (Alessie et al., 2011a), while literacy seems necessary to be able to understand and buy these products.

Future research can provide interesting extensions. First, the probabilities of misclassification can be made conditional on observed characteristics, such as education, changes in household composition or other factors. Second, we have not yet exploited the panel feature of the data; allowing for time-persistent or time-independent misclassification errors as in Dustmann and van Soest (2001) may yield valuable insights in how measurement errors should be prevented in a survey. Given the current results, both these extensions may well be preferred to the bivariate case, for which we need a restrictive assumption of conditional independence. Finally, we can analyze the effects of uncertainties in lifespan or pension income, measured using probabilistic survey questions as in Van Santen (2012), on the ownership rate of annuity products.

4.A Remaining probabilities in the likelihood function

$$\begin{aligned}
\mathbb{P}(y_1 = 1, y_2 = 0) &= \mathbb{P}(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 1)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) \\
&+ \mathbb{P}(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 0)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&+ \mathbb{P}(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 0, \tilde{y}_2 = 1)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
&+ \mathbb{P}(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 0, \tilde{y}_2 = 0)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 0) \\
&= [1 - \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \\
&- \mathbb{P}\left(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \\
&- \mathbb{P}\left(y_1 = 0, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right)] \, \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) \\
&+ \mathbb{P}\left(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 0, \tilde{y}_2 = 0\right) [1 - \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) \\
&- \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) - \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1)] \\
&+ \mathbb{P}(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 0)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&+ \mathbb{P}(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 0, \tilde{y}_2 = 1)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
&= \left[\alpha_1^2(1 - \alpha_1^1) - \alpha_0^1(1 - \alpha_0^2)\right] \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) + \alpha_0^1(1 - \alpha_0^2) \\
&+ \left[(1 - \alpha_0^2)(1 - \alpha_0^1 - \alpha_1^1)\right] \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&- \left[\alpha_0^1(1 - \alpha_0^2 - \alpha_1^2)\right] \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1)
\end{aligned}$$

$$\begin{aligned}
\mathbb{P}(y_1 = 0, y_2 = 1) &= \mathbb{P}(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 1)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) \\
&+ \mathbb{P}(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 0)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&+ \mathbb{P}(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 1)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
&+ \mathbb{P}(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 0)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 0) \\
&= [1 - \mathbb{P}\left(y_1 = 1, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \\
&- \mathbb{P}\left(y_1 = 1, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right) \\
&- \mathbb{P}\left(y_1 = 0, y_2 = 0 | \tilde{y}_1 = 1, \tilde{y}_2 = 1\right)] \, \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1)
\end{aligned}$$

$$
\begin{aligned}
&+ \mathbb{P}\left(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 0\right) \left[1 - \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1)\right. \\
&\left. -\ \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) - \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1)\right] \\
&+ \mathbb{P}(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 1, \tilde{y}_2 = 0)\mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&+ \mathbb{P}(y_1 = 0, y_2 = 1 | \tilde{y}_1 = 0, \tilde{y}_2 = 1)\mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1) \\
&= \left[\alpha_1^1(1 - \alpha_1^2) - \alpha_0^2(1 - \alpha_0^1)\right] \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 1) + \alpha_0^2(1 - \alpha_0^1) \\
&- \left[\alpha_0^2(1 - \alpha_0^1 - \alpha_1^1)\right] \mathbb{P}(\tilde{y}_1 = 1, \tilde{y}_2 = 0) \\
&+ \left[(1 - \alpha_0^1)(1 - \alpha_0^2 - \alpha_1^2)\right] \mathbb{P}(\tilde{y}_1 = 0, \tilde{y}_2 = 1)
\end{aligned}
$$

Chapter 5

Pension Wealth and Household Savings in Europe: Evidence from SHARELIFE*

* This chapter is based on Alessie, Angelini and Van Santen (2011).

5.1 Introduction

The demographic challenge of ageing populations has led and will lead European countries to reform their pension systems. For policymakers, understanding the effect that pension reforms will have on household and national saving is crucial. In particular, the effect of changes in pension wealth on private wealth is vital information for assessing the welfare effects of these reforms. A stylized version of the life–cycle model suggests that generous social security benefits will have a negative effect on the accumulation of private savings if households save only for retirement, i.e. crowding out of private wealth by pension wealth. However, the extent to which households offset pension wealth with other forms of wealth accumulation is difficult to gauge. From a theoretical point of view, the extent of the offset depends on a variety of other factors, such as the presence of binding liquidity constraints, the distortional effects of taxation and the fact that households might save for reasons other than retirement or may lack a basic level of financial literacy. From an empirical point of view, the econometric identification of the offset is made difficult by the lack of data on lifetime earnings and by the fact that pension wealth is typically measured with error in surveys.

In this paper we estimate whether and to what extent European households offset pension wealth with private savings. An innovative aspect of our paper is that we use retrospective data from the third wave of the Survey of Health, Ageing and Retirement in Europe (SHARELIFE), which collects information on the entire job and wage histories of older workers and retirees in 13 European countries. In this way we are able to construct measures for both the present value of past and future earnings and pension wealth at the individual level, a feature missing in most studies estimating the displacement effect.

Many papers have made attempts to estimate the displacement effect but the empirical evidence is mixed. In his seminal article, Feldstein (1974) uses aggregate time-series data for the US and shows that a 1 dollar in increase in Social Security Wealth (SSW) depresses private saving by about 40 dollar cents. However, Feldstein and Liebman (2002) point out that this estimate of the displacement effect might be inconsistent because of aggregation problems. For that reason many papers have used cross-section data to investigate the level of displacement between SSW and wealth (see e.g. Feldstein and Pellechio (1979), Dicks-Mireaux and King (1984), Hubbard (1986) and Jappelli (1995)). In these earlier studies non-pension wealth is typically regressed on cash earnings and pension wealth (and some other controls). Gale (1998) convincingly shows that in such regressions the estimated displacement effect is biased downwards. He proposes and applies a method to remove this bias, which boils down to multiply pension wealth by an age-specific adjustment factor, called "Gale's Q". He finds an estimated offset close to 100% for a sample of US households in which the head is employed and aged between 40 and 64. Attanasio and Rohwedder (2003) and Attanasio and Brugiavini (2003) use time series of cross-section data to estimate saving rate equations derived from life–cycle models, exploiting pension reforms in the United Kingdom and Italy respectively to identify the displacement effect. Their results indicate that the effects of pensions on wealth vary significantly across households, with nearly retired individuals showing more crowd out than young workers. Engelhardt and Kumar (2011) use data on 51-61 years old working individuals from the Health and Retirement Study (HRS) in the US and adopt an instrumental variables approach to account for measurement error in wealth and individual heterogeneity, such as taste for saving. They find an average displacement effect between 53 and 67 percent. However, quantile estimates show substantial heterogeneity across the wealth distribution, with crowd–in at lower quantiles, no offset at the median and significant crowd–out for affluent households. Kapteyn et al. (2005) exploit productivity differences across cohorts and the introduction of social security in the Netherlands to find a small but statistically significant displacement effect of 11.5%. Hurd et al. (2012) use cross-country variation and cross-sectional variation in education and marital status to identify the displacement effect on financial wealth from a pooled sample of retired males aged 65 to 75 from the HRS, ELSA (UK) and SHARE (ten continental European countries). To pool these samples, all variables are aggregated by education and marital status. Their estimated displacement effect ranges between 23 and 44 percent.

We contribute to the literature by presenting new estimates of the displacement effect using micro data on both older workers and retired individuals collected by the SHARELIFE project in 13 European countries. Opposite to Hurd et al. (2012) and like Gale (1998) and Engelhardt and Kumar (2011), we perform our analysis on a cross-section of households. Thanks to the retrospective nature of the data, we are able to construct a measure of the present value of past earnings using the entire job history of each respondent and the information on the first wage earned in each job. With the exception of Engelhardt and Kumar (2011), all previous studies instead had to rely on proxy measures for past earnings, most notably current income, age, education and marital status. Moreover, actual pension benefits for those that are retired allow us to construct pension wealth; for the non-retired, we use subjective information on individuals' expected retirement age and replacement rate to compute expected pension wealth. We show that the retrospective survey data are able to generate cross-country differences in wages and pensions, as well as age-earnings profiles that are in line with expectations.

An important econometric phenomenon both in this study and the empirical literature discussed above is the impact of measurement errors on the parameter estimates. Both pension wealth and the present value of past and future earnings are typically measured with error, if not unobserved. Typically, these two measurement errors are positively correlated with each other. We show in Section 5.2.1 that the bias which stems from those two positively correlated measurement errors, might well lead to a spurious positive partial correlation between pension wealth and private wealth. Therefore, we introduce a restricted model for which we can sign the impact of correlated measurement errors on the estimators. Furthermore, we provide lower bounds to the true offset using a sample of retirees, for whom we know lifetime income and pension wealth from two independent series of survey questions. Although both are measured with error, the correlation between these measurement errors is likely to be small or even negligible. We cannot make this claim for the non–retired included in the full sample, for whom we infer pension benefits from multiplying the (individual-specific) expected pension income replacement rate by current income, which essentially imposes correlation between the measurement errors.

The estimated displacement effect for the full sample is equal to 47.1% using robust regression and 60.9% using median regression techniques, and in both cases significantly different from zero and 100%. We obtain lower bounds between 17% and 30%, significantly different from zero. When we use financial wealth as the dependent variable instead of net worth, we estimate the crowd-out to be between 77.8% and 87.0%, and obtain a lower bound between 53% and 69%. Using the Instrumental Variable strategy of Chernozhukov and Hansen (2005,0) to avoid attenuation bias from measurement errors and unobserved heterogeneity, we obtain less precise estimates which suggest full displacement.

In the remainder of this paper, we first present a simple life-cycle model to guide our empirical analysis in Section 5.2. Section 5.3 discusses the variables used in this study and the assumptions we made in the computation of lifetime earnings and pension wealth. Section 5.4 presents the results and several robustness checks. Section 5.5 concludes.

5.2 Model

As most studies on this subject, we derive the equation of interest from a simple life–cycle model, which is the discrete–time counterpart of Gale (1998). Like Gale, we assume that past changes in the pension system have been fully anticipated by the agents at the beginning of their life. We ignore uncertainty and liquidity constraints, and assume perfect capital markets that produce a constant real interest rate, r. Moreover, we assume that the retirement age, R, and non capital income at age τ, y_τ, are exogenous variables. The within period utility function is assumed to be isoelastic (constant relative risk aversion [CRRA]). The consumer maximizes lifetime utility subject to the lifetime budget constraint, i.e:

$$\max_{c_\tau} \sum_{\tau=1}^{L} (1+\rho)^{1-\tau} \frac{c_\tau^{1-\gamma}}{1-\gamma} \tag{5.1a}$$

$$\text{s.t.} \sum_{\tau=1}^{L} (1+r)^{1-\tau} c_\tau = \sum_{\tau=1}^{L} (1+r)^{1-\tau} y_\tau = \sum_{\tau=1}^{R} (1+r)^{1-\tau} E_\tau + \sum_{\tau=R+1}^{L} (1+r)^{1-\tau} B_\tau \tag{5.1b}$$

where c_τ denotes consumption at age τ, E_τ pre–retirement earnings, B_τ pension benefits, ρ is the discount rate, L the maximum age and γ the coefficient of relative risk aversion. The first-order condition and the budget constraint characterize the consumption path:

$$c_\tau = c_1 \left(\left(\frac{1+r}{1+\rho} \right)^{1/\gamma} \right)^{\tau-1} \qquad \tau = 2, ..., L \tag{5.2a}$$

$$c_1 = \left(\sum_{\tau=1}^{L} \lambda^{\tau-1} \right)^{-1} \left(\sum_{\tau=1}^{L} (1+r)^{1-\tau} y_\tau \right) \tag{5.2b}$$

where $\lambda = \frac{((1+r)/(1+\rho))^{1/\gamma}}{1+r}$. By definition, wealth at the end of period t, A_t is equal to accumulated saving. Using (5.2a) and (5.2b), we can write this as

$$\begin{aligned} A_t &= \sum_{\tau=1}^{t} (1+r)^{t-\tau} (y_\tau - c_\tau) \\ &= \sum_{\tau=1}^{t} (1+r)^{t-\tau} y_\tau - Q(\lambda, t) \sum_{\tau=1}^{L} (1+r)^{t-\tau} y_\tau \end{aligned} \tag{5.3}$$

where

$$Q(\lambda, t) = \left(\frac{\sum\limits_{\tau=1}^{t} \lambda^{\tau-1}}{\sum\limits_{\tau=1}^{L} \lambda^{\tau-1}} \right) \tag{5.4}$$

is the so-called "Gale's Q" (see Gale (1998) and Engelhardt and Kumar (2011)). Using (5.1b), equation (5.3) can be rewritten as

$$A_t = \left(\sum_{\tau=1}^{t} (1+r)^{t-\tau} y_\tau - Q(\lambda, t) \sum_{\tau=1}^{R} (1+r)^{t-\tau} E_\tau \right) - Q(\lambda, t) \sum_{\tau=R+1}^{L} (1+r)^{t-\tau} B_\tau \tag{5.5}$$

The term $\sum\limits_{\tau=R+1}^{L} (1+r)^{t-\tau} B_\tau$ denotes pension wealth at age t, i.e. the present value of pension benefits.

5.2.1 Empirical implementation

Expression (5.5) leads to the following equation to be estimated for the sample of retired and non-retired individuals:

$$A_t = \beta_0 + \beta_1 z_{1t}^* + \beta_2 z_{2t}^* + \boldsymbol{x}_t' \gamma + \varepsilon_t \tag{5.6}$$

where

$z_{1t}^* = \sum\limits_{\tau=1}^{t} (1+r)^{t-\tau} y_\tau - Q(\lambda, t) \sum\limits_{\tau=1}^{R} (1+r)^{t-\tau} E_\tau$

$z_{2t}^* = Q(\lambda, t) \sum\limits_{\tau=R+1}^{L} (1+r)^{t-\tau} B_\tau$ ("Q adjusted pension wealth")

$\boldsymbol{x}_t$= a vector of demographic household characteristics that might affect savings.

The main parameter of interest is β_2, which measures the extent of displacement between discretionary household wealth and pension wealth. The canonical life–cycle model sketched above predicts full displacement ($\beta_2 = -1$) and $\beta_1 = 1$. However, the extent of displacement might be smaller because of factors which are not considered in the canonical model such as (binding) liquidity constraints, uncertainty, endogeneity of the retirement decision and lack of financial literacy.

Gale (1998) and Engelhardt and Kumar (2011) also use equation (5.6) as the basis of their empirical work. In the earlier literature (see e.g. Jappelli (1995) and Hubbard (1986)) the pension wealth variable is typically not interacted with the adjustment factor Q. Gale (1998) points out that this might lead to a considerable underestimation of the crowding out effect. At the same time, Gale (1998, p. 711) shows that the Q-adjustment is also valid even if the true model does not embody perfect offset.

One of the attractive features of the SHARE survey is that it contains sufficient retrospective and prospective information to proxy the variables z_{1t}^* and z_{2t}^* in a convincing way without relying on too many arbitrary assumptions. Gale (1998), who uses the 1983 wave of the Survey of Consumer Finances (SCF), instead does not observe directly the present value of past and current earnings (i.e the first term of z_{1t}). He therefore replaces the z_{1t}^* regressor in equation (5.6) with the following variables: current income, age of the head of household and his/her spouse and earnings interacted with age and other demographic factors.[1] This approximation procedure, which is also used in many other studies, might provide rather imprecise proxies and consequently might lead to an inconsistent estimate of the displacement effect. As far as we know, Engelhardt and Kumar (2011) is the only other study to use a direct measure for the present value of past earnings, which stems from administrative records and is consequently precisely measured.

As we said before, our empirical specification is based on a very stylized version of the life cycle model. Blau (2011) formulates a richer economic model which takes into account, amongst other things, endogenous retirement choice, uncertainties and stochastic income profiles. He uses his model to generate a simulated dataset on which he fits the linear specification of Gale. He finds that this linear model over–estimates the crowd-out effect. However, Blau shows that the coefficient for pension wealth is much closer to the true displacement effect, if one adds lagged wealth to the static model of Gale. The advantage of the dynamic specification is that it controls for initial conditions such as the present value of past earnings. We believe that our model is more similar to the dynamic specification because we

[1] In Appendix 5.B, we show the results when applying Gale (1998)'s method to the SHARE dataset. We obtain positive but insignificant estimates of the displacement effect, contrary to Gale. Our result can be explained by the presence of correlated measurement errors in income and pension wealth, as we detail in Appendix 5.B. For the SCF, such a problem does not occur.

control for lifetime earnings in the equation.

Our first results were rather disappointing and completely refuted the basic life–cycle model: we found a negative OLS estimate for β_1 and a positive estimate for β_2. However, we argue that these results could be driven by serious measurement error problems: instead of z_1^* and z_2^{*2}, we observe the error ridden variables z_1 and z_2:

$$z_k = z_k^* + \eta_k, \;\; k = 1, 2 \tag{5.7}$$

As we explain in more detail in Section 5.3, there are two main reasons for measurement errors in these variables. First, the wage earned (or pension benefit received) may be reported incorrectly. Second, we interpolate the wages and extrapolate pension benefits to compute the lifetime wage path and pension wealth, which is obviously a simplification of reality. Moreover, it is rather likely that in our data the measurement errors η_1 and η_2 are positively correlated with each other: $Cov(\eta_1, \eta_2) \geq 0$. On top of this we make the following assumptions about the measurement errors:

- $E(\eta_k z_k^*) = E(\eta_k \varepsilon) = E(\eta_k) = 0, \;\; k = 1, 2$
- $E(\eta_k \boldsymbol{x}) = \boldsymbol{0}, \;\; k = 1, 2$
- $E(\eta_1 z_2^*) = E(\eta_2 z_1^*) = 0$
- $Var(\eta_k) = \sigma_{\eta_k}^2, \; k = 1, 2; \;\; Cov(\eta_1, \eta_2) = \sigma_{\eta_1 \eta_2} \geq 0$ (homoskedasticity)

Substitution of equation (5.7) into (5.6) yields

$$A = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \boldsymbol{x}'\boldsymbol{\gamma} + \varepsilon - \beta_1 \eta_1 - \beta_2 \eta_2 \tag{5.8}$$

The linear projection $\hat{E}^*(A|1, z_1, z_2, \boldsymbol{x})$ is equal to

$$\begin{gathered}\hat{E}^*(A|1, z_1, z_2, \boldsymbol{x}) = \beta_0 + \beta_1 z_1 + \beta_2 z_1 + \boldsymbol{x}'\boldsymbol{\gamma} + \hat{E}^*(\varepsilon|1, z_1, z_2, \boldsymbol{x}) - \\ \beta_1 \hat{E}^*(\eta_1|1, z_1, z_2, \boldsymbol{x}) - \beta_2 \hat{E}^*(\eta_2|1, z_{1t}, z_{2t}, \boldsymbol{x})\end{gathered} \tag{5.9}$$

Given our assumptions on the measurement errors, one can easily show that $\hat{E}^*(\varepsilon|1, z_1, z_2, \boldsymbol{x}) = 0$. So the biases, if any, are equal to $-\beta_1 \hat{E}^*(\eta_1|1, z_1, z_2, \boldsymbol{x}) - \beta_2 \hat{E}^*(\eta_2|1, z_1, z_2, \boldsymbol{x})$. Let

[2] From now onwards, we drop the t index for notational convenience.

$(\theta^k_{z_1}, \theta^k_{z_2}, \boldsymbol{\theta}^k_{\boldsymbol{x}})$ be the projection coefficients of $(z_1, z_2, \boldsymbol{x})$ in $\hat{E}^*(\eta_k|1, z_1, z_2, \boldsymbol{x})$, $k = 1, 2$. By the projection formula (see Hayashi (2000, Section 2.9)):

$$\begin{pmatrix} \theta^1_{z_1} \\ \theta^1_{z_2} \\ \boldsymbol{\theta}^1_{\boldsymbol{x}} \end{pmatrix} = \begin{pmatrix} Var(z_1) & Cov(z_1, z_2) & Cov(z_1, \boldsymbol{x}') \\ Cov(z_2, z_1) & Var(z_2) & Cov(z_2, \boldsymbol{x}') \\ Cov(\boldsymbol{x}, z_1) & Cov(\boldsymbol{x}, z_2) & Var(\boldsymbol{x}) \end{pmatrix}^{-1} \begin{pmatrix} Cov(z_1, \eta_1) \\ Cov(z_2, \eta_1) \\ Cov(\boldsymbol{x}, \eta_1) \end{pmatrix} \tag{5.10}$$

Given our assumptions, $Cov(z_2, \eta_1) = \sigma_{\eta_1\eta_2} \geq 0$ and $Cov(\boldsymbol{x}, \eta_1) = \mathbf{0}$. Obviously, $Cov(z_1, \eta_1) = Var(\eta_1) = \sigma^2_{\eta_1}$. Therefore, the projection coefficients can be rewritten as

$$\begin{pmatrix} \theta^1_{z_1} \\ \theta^1_{z_2} \\ \boldsymbol{\theta}^1_{\boldsymbol{x}} \end{pmatrix} = \sigma^2_{\eta_1} \boldsymbol{a}_1 + \sigma_{\eta_1\eta_2} \boldsymbol{a}_2 \tag{5.11}$$

where $\boldsymbol{a}_1$ and $\boldsymbol{a}_2$ are respectively the first and second column of the inverse variance-covariance matrix

$$\begin{pmatrix} Var(z_1) & Cov(z_1, z_2) & Cov(z_1, \boldsymbol{x}') \\ Cov(z_2, z_1) & Var(z_2) & Cov(z_2, \boldsymbol{x}') \\ Cov(\boldsymbol{x}, z_1) & Cov(\boldsymbol{x}, z_2) & Var(\boldsymbol{x}) \end{pmatrix}^{-1}$$

Likewise

$$\begin{pmatrix} \theta^2_{z_1} \\ \theta^2_{z_2} \\ \boldsymbol{\theta}^2_{\boldsymbol{x}} \end{pmatrix} = \sigma^2_{\eta_2} \boldsymbol{a}_2 + \sigma_{\eta_1\eta_2} \boldsymbol{a}_1 \tag{5.12}$$

Therefore the biases in the OLS estimators $\hat{\beta}^{OLS}_1$ and $\hat{\beta}^{OLS}_2$ are equal to

$$\begin{aligned} \text{plim } \hat{\beta}^{OLS}_1 - \beta_1 &= -\beta_1(\sigma^2_{\eta_1} a_{11} + \sigma_{\eta_1\eta_2} a_{21}) - \beta_2(\sigma^2_{\eta_2} a_{21} + \sigma_{\eta_1\eta_2} a_{11}) \\ &= -(\beta_1\sigma^2_{\eta_1} + \beta_2\sigma_{\eta_1\eta_2}) a_{11} - (\beta_2\sigma^2_{\eta_2} + \beta_1\sigma_{\eta_1\eta_2}) a_{21} \end{aligned} \tag{5.13}$$

and

$$\begin{aligned} \text{plim } \hat{\beta}^{OLS}_2 - \beta_2 &= -\beta_2(\sigma^2_{\eta_2} a_{22} + \sigma_{\eta_1\eta_2} a_{21}) - \beta_1(\sigma^2_{\eta_1} a_{21} + \sigma_{\eta_1\eta_2} a_{22}) \\ &= -(\beta_2\sigma^2_{\eta_2} + \beta_1\sigma_{\eta_1\eta_2}) a_{22} - (\beta_1\sigma^2_{\eta_1} + \beta_2\sigma_{\eta_1\eta_2}) a_{21} \end{aligned} \tag{5.14}$$

The direction of the asymptotic bias in the OLS estimator $\hat{\beta}_1^{OLS}$ depends on the signs of the elements in the vector $\boldsymbol{a}_1$. The first element of $\boldsymbol{a}_1$, a_{11}, is unambiguously positive (it is a diagonal element of the inverse of a variance-covariance matrix). The second element a_{21} is presumably negative because one would expect that $Cov(z_1, z_2) > 0$ and that the correlation between (z_1, z_2) and $\boldsymbol{x}$ is not unusually large. In our data $\hat{a}_{21}$ is indeed negative. Equation (5.13) suggests that under the validity of the simple life–cycle model ($\beta_2 = -1$ and $\beta_1 = 1$) and under the (plausible) assumptions

$$\sigma_{\eta_1\eta_2} < \sigma_{\eta_1}^2 \tag{5.15a}$$

$$\sigma_{\eta_1\eta_2} < \sigma_{\eta_2}^2 \tag{5.15b}$$

the OLS estimator $\hat{\beta}_1^{OLS}$ is downward biased. The first term on the right hand side of equation (5.13), $(-(\beta_1\sigma_{\eta_1}^2 + \beta_2\sigma_{\eta_1\eta_2})a_{11})$ depicts the usual (downward) attenuation bias. The second term on the right hand side of equation (5.13) reveals that, since $\hat{a}_{21}$ is actually smaller than zero, the measurement error in z_{2t} aggravates the downward bias in $\hat{\beta}_1^{OLS}$. The estimator could even converge in probability to a negative number! Along the same line of reasoning one can argue that $\hat{\beta}_2^{OLS}$ is upward biased and that the upward bias in this OLS estimate is exacerbated by the measurement error in z_1. As we said before, we find that the OLS estimate of β_2 is positive. In other words, measurement error problems could drive the estimation results indicated above.[3] The OLS estimate of the displacement effect presented by Engelhardt and Kumar (2011) also suggests pensions wealth crowds in non–pension wealth. We believe that their OLS estimate of the displacement effect is severely upward biased because the measurement errors in their right hand side variables "current earnings" and "Q adjusted pension wealth" are likely to be positively correlated.[4]

[3] This line of reasoning extends directly to applying Gale (1998)'s method, as we document in Appendix 5.B.

[4] Engelhardt and Kumar (2011) ignore the second term in z_{1t}^* $(Q(\lambda, t) \sum_{\tau=1}^{R} (1+r)^{t-\tau} E_\tau)$ but proxy this regressor by a survey measure of current earnings, age, expected retirement age and region of birth plus some interaction terms. They address the measurement error in the pension wealth variable by adopting IV estimation. However, they do not take into account that the measurement error in current earnings might affect their estimate of the displacement effect.

In order to be able to sign the bias associated with the measurement error problem, we impose the restriction $\beta_1 = 1$ in the estimation. In other words, we estimate the following model instead of equation (5.8):

$$A - z_1 = \beta_0 + \beta_2 z_2 + \boldsymbol{x}'\gamma + \varepsilon - \eta_1 - \beta_2 \eta_2 \tag{5.16}$$

It is easy to show that in this case the bias in the OLS estimator $\hat{\beta}_2^{OLS}$ is equal to

$$\text{plim } \hat{\beta}_2^{OLS} - \beta_2 = -(\sigma_{\eta_1\eta_2} + \beta_2 \sigma_{\eta_2}^2)\tilde{a}_{11} \tag{5.17}$$

where $\tilde{a}_{11}$ is the first diagonal element of the inverse variance-covariance matrix

$$\begin{pmatrix} Var(z_2) & Cov(z_2, \boldsymbol{x}') \\ Cov(\boldsymbol{x}, z_2) & Var(\boldsymbol{x}) \end{pmatrix}^{-1}$$

Obviously, $\tilde{a}_{11} > 0$. In case of 1) full displacement ($\beta_2 = -1$), 2) zero correlation between $\boldsymbol{x}$ and z_2, 3) nonnegatively correlated measurement errors ($\sigma_{\eta_1\eta_2} \geq 0$) and 4) under assumption (5.15b), equation (5.17) implies that the OLS estimate for β_2 is upward biased and that $-1 < \text{plim}\, \hat{\beta}_2^{OLS} < 0$.[5] If there is only partial displacement ($-1 < \beta_2 < 0$), we cannot determine the direction (upward or downward) of the bias in the OLS estimate. In the empirical section we will carry out a sensitivity analysis in which we estimate model (5.16) on the subsample of retirees. As we will explain in the next section, for this subsample the measurement errors in z_{1t}^* and z_{2t}^* are likely to be uncorrelated ($\sigma_{\eta_1\eta_2} = 0$). In that case, the estimate of the displacement coefficient will be attenuated irrespective of the true value of β_2. However, we still learn something from the estimation using both retired and non-retired individuals. Even in the presence of measurement error in pension wealth we would

[5] To see this, note that if $\beta_2 = -1$ we can write the right hand side of equation (5.17) as

$$\frac{\sigma_{\eta_2}^2 - \sigma_{\eta_1\eta_2}}{Var(z_2)} \tilde{a}_{11} Var(z_2) \tag{5.18}$$

If we additionally assume zero correlation between $\boldsymbol{x}$ and z_2 ($\tilde{a}_{11} \times Var(z_2) = 1$) and $0 \leq \sigma_{\eta_1\eta_2} < \sigma_{\eta_2}^2$, then $0 < \frac{\sigma_{\eta_2}^2 - \sigma_{\eta_1\eta_2}}{Var(z_2)} = \frac{\sigma_{\eta_2}^2 - \sigma_{\eta_1\eta_2}}{Var(z_2^*) + \sigma_{\eta_2}^2} < 1$ and consequently $-1 < \text{plim}\, \hat{\beta}_2^{OLS} < 0$. In our data, the correlation between z_2 and $\boldsymbol{x}$ is low enough, as we find that $\tilde{a}_{11} \times Var(z_2) = 1.30 \times 0.68 = 0.884$, and hence equations (5.17) and (5.18) imply that $0 < \text{plim } \hat{\beta}_2^{OLS} + 1 < 1$, or $-1 < \text{plim } \hat{\beta}_2^{OLS} < 0$.

expect that the estimate of the displacement coefficient is negative.[6]

In order to address the measurement error problem, one could opt for IV estimation as in Engelhardt and Kumar (2011). Like Attanasio and Brugiavini (2003) and Attanasio and Rohwedder (2003), they point out that Q adjusted pension wealth should be instrumented for other reasons, such as omitted variable bias resulting from unobserved heterogeneity. For instance, some 'patient' households may have a high taste for saving. We pursue this strategy in Section 5.4.1. In all cases, to limit the impact of outliers (e.g. due to measurement error), we use robust and median regression techniques to estimate β_2 and γ.

5.3 Data

In our empirical analysis we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE). The SHARE project started with wave 1 in 2004/05, collecting information on the current socio–economic status (income, wealth, housing), health and expectations of European individuals aged 50 and over and their partners. A first longitudinal follow–up was collected with wave 2 in 2006/7, when new countries joined the project and a refresher sample was added to maintain the representativeness of the survey. In 2008/2009 the third wave of data collection, known as SHARELIFE, asked all previous respondents (waves 1 and 2) and their partners to provide information not on their current situation but on their entire life–histories. The retrospective information ranges from childhood health to relationships to housing to work careers.[7] SHARELIFE interviewed 15,170 females and 11,666 males in 17,901 households and was conducted in thirteen European countries: Austria, Germany, Sweden, the Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, the Czech Republic and Poland.

Our analytical sample consists of 3,590 males born between 1931 and 1952, aged

[6] This can be seen as follows: if $0 \leq \sigma_{\eta_1\eta_2}$ equation (5.17) implies that:

$$\text{plim } \hat{\beta}_2^{OLS} = \beta_2(1 - \sigma^2_{\eta_2}\tilde{a}_{11}) - \sigma_{\eta_1\eta_2}\tilde{a}_{11} < \beta_2\left(1 - \frac{\sigma^2_{\eta_2}}{Var(z_2)}\tilde{a}_{11}Var(z_2)\right) \tag{5.19}$$

In our data $0 < \left(1 - \frac{\sigma^2_{\eta_2}}{Var(z_2)}\tilde{a}_{11}Var(z_2)\right) < 1$ because $\tilde{a}_{11}Var(z_2) = 0.884$ (see footnote 5). Therefore equation (5.19) implies that plim $\hat{\beta}_2^{OLS} < 0$ if there is any displacement ($\beta_2 < 0$).

[7] Börsch-Supan et al. (2011) characterizes the data and presents the first descriptive statistics.

55-75 in the interview year of wave 2. We restrict the sample to males as we would need to make many assumptions for broken careers, typical for women with children. The literature discussed in Section 5.1 focuses on males as well. In our sample selection, we drop those individuals who never worked or did not report any wage in SHARELIFE (2,012 cases), and respondents aged below 55 or above 75 (2,581 cases) to have a sample consisting of individuals around retirement. We keep persons that have been self-employed at any stage during their career, but drop those that worked for less than 20 years (97 cases) to exclude the disabled. We exclude males for whom only one wage point is available (1,670 cases), and retirees with missing pension benefits or workers with missing expected replacement rates (1,592 cases). We trim compounded labour income and pension wealth by 1% from above and below in each country to end up with our final sample of 3,590 observations. All monetary amounts are expressed in PPP-adjusted 2006 German Euros, irrespective of in which country and in which year these amounts were earned. To estimate equation (5.16), we compute the following variables.

- *Non–pension wealth*, A_t, is mostly obtained from wave 2. We resort to information from wave 1 only for those individuals who dropped out of the survey in wave 2 but were then retrieved in SHARELIFE. In our analysis we use both household net worth and net financial wealth as dependent variables. According to Gale (1998, p. 713) a narrow measure of non–pension wealth, such as financial wealth, may be unable to detect much of the displacement, as pension wealth is accumulated over a long period. On the other hand, Hurd et al. (2012, p. 10) argue that financial wealth is more liquid than real wealth and hence more prone to being displaced by pension wealth. Our measure of net financial wealth is equal to gross financial assets (bank accounts, government and corporate bonds, stocks, mutual funds, individual retirement accounts, contractual savings for housing and the face value of life insurance policies) minus financial liabilities. Net worth is the sum of net financial wealth and real wealth, where the latter is the sum of the value of the primary residence net of the mortgage, the value of other real estate, owned share of own business and owned cars. Missing values for each of the components of wealth are replaced by five simulated versions, following multiple imputation techniques (Christelis, 2011). In total, for 56% of the analytical sample one of the separate components of net worth has been imputed, although for less than 15% of the sample more than one component was imputed. All equations are estimated using multiple imputations techniques.

- *Compounded labour income*, $z_{1t} = \sum_{\tau=1}^{t} (1+r)^{t-\tau} E_\tau$, is calculated from SHARELIFE. The job history section in SHARELIFE asks the respondents to provide start and end dates of each job the respondent has held, as well as the first monthly wage after taxes. For the self-employed, monthly income from work after taxes is asked instead. The respondent also identifies his main job during his career. For the retirees, the last monthly net wage (or, for the self-employed, net income from work) of the main job is asked. For those that are still employed at the time of the SHARELIFE interview, the current wage is asked instead. We use the data to construct a panel with one observation per year per individual, from birth to the wave 2 interview year. The wage path is obtained using linear interpolation between the first wage on each job, the last wage of the main job and the current wage for the employed. For those still working in wave 2, we use the wage in that year as an additional point on the wage path.[8] As for non–pension wealth, these wages have been imputed in case of missing values (9%). During unemployment years, we assign the respondent a wage equal to 80% of their last earnings. We convert all incomes to annual PPP-adjusted German Euros of 2006 following the procedure explained in Trevisan et al. (2011). Period 1 is taken to be the start of the working career, and we compound up to the wave 2 interview year for the employed[9], and the year before receiving retirement benefits for the retired[10],

[8] One important difference between the first two survey waves is that wages and pensions were elicited gross (before taxes) in wave 1, and net in wave 2, which is why we only use wave 2 information to generate our main variables.

[9] We use the term employed to denote the non-retired, although it is not necessary to be actually employed in wave 2 due to e.g. unemployment. Also, this term includes the currently self-employed.

[10] For the retired, this means that the dependent variable is $A_t - z_{1R}$, and hence these two components are measured at different ages. We made this assumption to prevent correlated measurement errors, which would otherwise (using $A_t - z_{1t}$) obviously arise for the retired subsample. Moreover, we have selected respondents around retirement, which means this assumption should not much affect our results.

using an annual real interest rate of 3%, as in Hurd et al. (2012) and Attanasio and Rohwedder (2003). After compounding, we have a cross-sectional dataset, with one observation per individual, as observed in the interview year of wave 2.

- *Future labour income*, $\sum_{\tau=t+1}^{R}(1+r)^{t-\tau}E_{\tau}$, which needs to be calculated only for the employed sample, is computed under the assumption of constant real wages ($y_{\tau} = y_t \quad \tau = t+1, ..., R$). Retirement starts in the in which the individual reaches his expected retirement age, obtained from wave 2, or the statutory retirement age (65 in each country except France (60) and Czech Republic (62) in 2007, as reported in Angelini et al. (2009)) in case of item non-response to that question. We use country-specific 2006 life tables from the Human Mortality Database (www.mortality.org) to weight all future incomes by the probability of survival.

- *Pension wealth*, $z_{2t} = \sum_{\tau=R+1}^{L}(1+r)^{t-\tau}B_{\tau}$, for the retired is calculated under the assumption of constant real pension benefits, which is more or less in line with pension systems in the countries we study. The level of benefits is taken primarily from SHARELIFE, and wave 2 pension benefits are used in case of item non-response (13% of the analytical sample). For the employed, we use the expected replacement rate[11] from wave 2, multiplied by current wage, to obtain expected pension benefits[12]. Again, all future incomes are weighted by survival rates and we assume a maximum age of 110.

- *Pension wealth adjustment*, $Q(\lambda, t)$ is computed using expression 5.4, with $r = \rho = 0.03$ (or $\lambda = 1.03^{-1}$).

- *Explanatory variables*, $\boldsymbol{x}_t$, include a set of indicator variables to capture differences across households. Specifically, we include an indicator for higher

[11] The exact question to elicit the expected replacement rate for old age pensions, occupational pensions or early retirement benefits is stated as follows: "Please think about the time in which you will start collecting this pension. Approximately, what percentage of your last earnings will your pension amount to?". We take the maximum replacement rate from these pension categories as the individual's expected replacement rate. Given our age selection (55-75), we believe that the employed respondents provide sensible answers to this question.

[12] For those that retired between waves 2 and 3, we take their pension benefit as reported in SHARELIFE.

education (ISCED ≥ 4, post-secondary and tertiary education), medium education (ISCED=3, secondary education), aged 55-60, aged 70-75, married, no children, self-reported bad health, second earner in the household, and spells without work during the career. In other specifications, we control additionally for inheritances received in the past using both an indicator and the amount; an indicator for being retired; or characteristics (education and health) of the spouse. All regressions have a full set of country fixed effects, with Germany as the base country.

We emphasize that compounded labour income and pension wealth, z_{1t} and z_{2t}, for the retired subsample are computed from two different sets of questions. Therefore, while both are likely measured with error, these errors are less likely to be correlated. For the working, by using the expected replacement rate, pension wealth is nearly a linear function of current income, with a sample correlation of 0.83, and hence the measurement errors are likely correlated. We use this observation to conduct a sensitivity analysis in Section 5.4 by selecting only the retired subsample.

5.3.1 Sample characteristics

Table 5.1 shows sample statistics for the two main variables obtained from the retrospective survey, annual labour income and annual pension income, as well as for net worth and financial wealth, by country and work status. We compute average annual labour income as the sum of all annualized wages divided by years worked[13]; annual pension income is equal to the sum of pension incomes until death divided by remaining life expectancy.[14] We emphasize that the amounts reported here are for one earner only, hence household labour income or pension income is likely to be higher. Furthermore, the amounts, although corrected for inflation and currency devaluations, could have been earned already in the 1950's, and hence are relatively low compared to current earnings. The cross-country pattern of median labour incomes is encouraging, we believe, for the reliability of retrospective data; countries like Poland and the Czech Republic have considerably

[13] Note that this is similar to our measure of compounded labour income, using $r = 0$ instead, and dividing by years worked.

[14] Remaining life expectancy is calculated using the country-specific mortality rates, conditioning on survivorship until the real age at the wave 2 interview year.

lower wages and pensions compared to Western European countries, while wages and pensions in Switzerland are higher. Table 5.1 also makes clear that there are likely to be cohort effects in earnings and, via the replacement rate, in pensions: those still working in the wave 2 interview year have substantially higher wages and pensions than those already retired.

Table 5.1. Medians by country and retirement status

Country	Annual labour income		Annual pension income		Wealth		Observations
	Working	Retired	Working	Retired	Net worth	Financial	
Austria	20,786	16,236	21,151	13,209	180,990	17,698	123
Germany	24,226	17,922	21,999	11,669	221,174	36,426	365
Sweden	24,747	20,765	16,046	12,272	206,176	57,980	341
Netherlands	23,810	16,526	24,122	11,973	222,288	39,273	334
Spain	16,954	15,603	19,710	9,149	302,695	6,827	176
Italy	17,255	12,650	14,421	9,853	212,103	8,169	486
France	26,268	24,582	18,400	15,516	325,397	36,672	256
Denmark	23,778	19,153	14,701	9,524	216,381	69,687	328
Greece	22,914	16,304	16,695	12,939	216,650	2,917	119
Switzerland	38,930	33,455	25,051	20,434	305,083	99,882	221
Belgium	22,559	18,552	18,258	12,968	304,183	54,116	398
Czech Republic	11,375	9,369	8,226	5,794	107,005	8,218	305
Poland	8,507	8,056	7,754	5,349	58,597	1,946	138
Total	22,733	16,441	17,016	10,723	217,488	25,672	3,590

Table shows the median values for annualized labour and pension incomes obtained from the retrospective survey, by country and retirement status, as well as the levels of wealth obtained from wave 2.
All amounts are in PPP-adjusted German Euros of 2006.

We also investigate the dynamic properties of earnings by estimating age-earnings profiles by country group: North represents Sweden, Denmark and the Netherlands, Mid-West includes Austria, Germany, Switzerland, France and Belgium, South includes Spain, Italy and Greece and East represents Poland and Czech Republic. In particular, we estimate a regression of the log of monthly real wage (in €1,000) on a 4^{th}-order polynomial in age, for both low and high educated individuals. We use a fixed-effects specification to deal with unobserved heterogeneity. Figure 5.1 shows the implied age-earnings profiles. Earnings for low-educated individuals are lower than for high-educated persons, as expected. Moreover, we observe a more hump-shaped profile for high-educated, with wages rising faster in early ages. From what we know from earlier literature, these patterns are not surprising, and provide evidence in favor of retrospective earnings information.[15]

[15] We do not correct for cohort effects and labor supply effects (e.g. reduced hours of work later in life).

Figure 5.1. Age-earnings profiles by education level

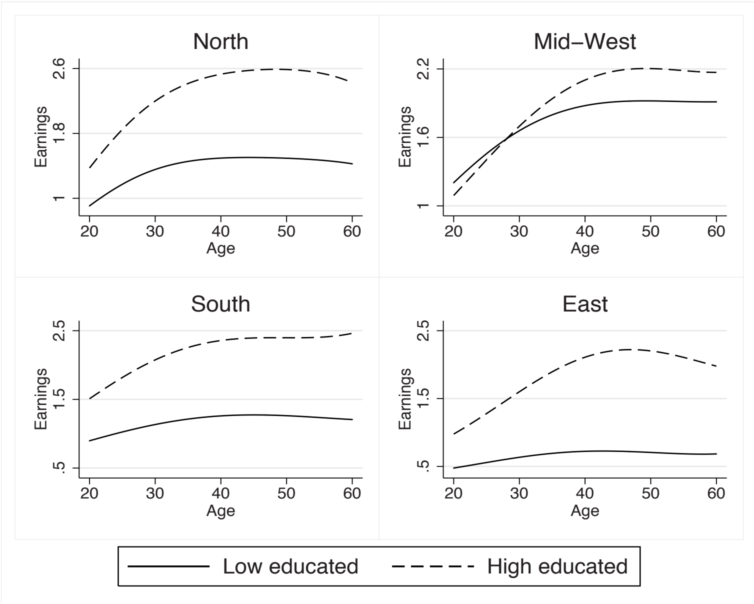


Table 5.2 shows sample statistics for the remaining variables used in this study. 69% of the sample is retired at the time of the wave 2 interview, while only 0.3% is unemployed. On average, the males in our analytical sample have only one year of unemployment, and have been working for 40 years. The vast majority is married, and 61% have a second earner in the household.

Given our sample selection (20 year-of-birth cohorts and men with at least 20 years of work experience), these are not likely to distort the age-earnings profiles much.

Table 5.2. Sample characteristics

Variable	Mean	SD
Age	63.7	5.5
% Retired	69.3	
% Working	30.4	
Actual retirement age (retired)	59.1	4.6
Expected retirement age (working)	63.2	2.5
Actual replacement rate (%, retired)	70.1	35.0
Expected replacement rate (%, working)	66.4	17.4
Years worked	40.3	5.5
Years not worked	1.2	2.6
Gale's Q	0.5	0.1
% High educated	29.7	
% Medium educated	33.4	
% Married	88.2	
% Second earner	61.3	
% Bad health	26.2	
% Inheritance received	36.4	
Amount inherited ($\times$ €$1,000$)	14.2	49.4

Table shows the mean and standard deviation of household characteristics. N=3,590 except for retired (N=2,487) or working (N=1,103) specific variables.

5.4 Results

We estimate the model represented in equation (5.16) both using robust regression and median regression techniques, as Gale (1998) does. Since wages and pension benefits from wave 2 and the measures of non–pension wealth have been imputed five times in case of missing values, we use multiple imputation techniques to obtain the correct coefficients and standard errors (Little and Rubin, 2002).[16] The results are presented in Table 5.3. Our controls include two age dummies[17], marital status, presence of children, education, health, the country of residence and indicators for whether in the family there has been a second income earner and whether there were years of unemployment in the working career, as well as country fixed effects (see Table 5.A.1). For median regression, standard errors are based on 1000 bootstrap replications.

[16] If $\hat{\beta}_m$ and $\hat{V}_m$ denote the vector of parameter estimates and variance matrix for imputation m, respectively, the estimates equal $\hat{\beta} = \frac{1}{5}\sum_{m=1}^{5}\hat{\beta}_m$ with variance matrix $\hat{V} = \frac{1}{5}\sum_{m=1}^{5}\hat{V}_m + \frac{3}{10}\sum_{m=1}^{5}\left(\hat{\beta}_m - \hat{\beta}\right)\left(\hat{\beta}_m - \hat{\beta}\right)'$, which takes into account both within- and between-imputation variance.

[17] As we estimate a cross-sectional regression, we cannot distinguish between age, cohort and time effects.

Table 5.3. Estimates of the displacement effect

	Robust regression			Median regression		
Variables	(1) Full sample	(2) Retired sample	(3) Old sample	(4) Full sample	(5) Retired sample	(6) Old sample
Pension wealth	-0.471***	-0.205**	-0.173*	-0.609***	-0.296	-0.306*
	(0.0878)	(0.0936)	(0.0965)	(0.151)	(0.180)	(0.177)
Observations	3590	2487	2415	3590	2487	2415
p-value $\beta_2 = -1$	0.000	0.000	0.000	0.011	0.000	0.000
p-value Country effects	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Bootstrapped standard errors for median regression, 1000 replications.

Our results for the full sample imply an estimated offset[18] between 47.1% and 60.9% depending on the estimation method: the offset is significantly different from zero at all conventional levels and significantly different from 100%, although not at the 1% level in the case of median regression (columns (1) and (4) of Table 5.3). As Gale (1998), we also find that robust regression estimates of the offset are qualitatively the same as median regression estimates but quantitatively smaller. The control variables are mainly insignificant, with the exception of the indicator for gaps in the career, resulting in less wealth, and strongly significant age effects. Although insignificance of, for example, education may seem surprising, we emphasize that education correlates with compounded labour income, included in our regressions. The country-fixed effects are highly significant.

As argued in Section 5.2.1, the estimates for the full sample are likely to be biased, away from zero due to the fact that measurement errors in z_{1t} and z_{2t} are possibly correlated for the non–retired (cf. equation (5.17)) and towards zero due to measurement error in pension wealth. Since these biases work in opposite direction, we can only hope that these balance out on aggregate. In columns (2) and (5) we report the estimated crowd-out for the group of retirees. For this group, as argued above, the correlation between the measurement errors in compounded labour income and pension wealth (i.e. $\sigma_{\eta_1 \eta_2}$ from Section 5.2.1) should be considerably smaller or even negligible for this group, and hence, the estimate should only be affected by attenuation bias due to measurement error in pension wealth. Therefore, we can consider the estimates for the group of retirees as a lower bound for

[18] The offset is simply the negative of the estimated coefficient for pension wealth.

the true offset. Indeed, we find that the attenuation bias gives parameter estimates towards zero, and hence a lower estimated offset compared to the full sample results. The estimated displacement effect is significantly different from zero only with robust regression.

One issue with selecting the sample of retirees is that, although we do not explicitly model the retirement decision, it might be endogenous. Therefore, in columns (3) and (6), we do not select the sample based on retirement status, which could lead to endogenous sample selection and hence inconsistent parameter estimates, but using an age criterion: those aged 60 or below are dropped independent of retirement status (in our sample average retirement age is 59.1, see Table 5.2). In the remaining group of 2415 males, around 90% is retired, compared to 70% in our baseline results. Effectively, for this old sample, the effect of correlated measurement errors should be similar to selecting only the retirees, which is confirmed by the parameter estimates. The estimated offset is between 17.3% and 30.6%, and is significantly different from zero at the 10% level. [19]

Table 5.4. Robustness checks displacement effect

Variables	(1) Financial wealth, full	(2) Financial wealth, retired	(3) Financial wealth, old	(4) Inheritances received	(5) Partner's characteristics	(6) Low educated	(7) High educated	(8) No occupational pensions
Robust regression	-0.778***	-0.614***	-0.532***	-0.527***	-0.488***	-0.215*	-0.833***	-0.380***
	(0.0738)	(0.0734)	(0.0779)	(0.0877)	(0.0876)	(0.122)	(0.153)	(0.121)
p-value $\beta_2 = -1$	0.003	0.000	0.000	0.000	0.000	0.000	0.277	0.000
Median regression	-0.870***	-0.692***	-0.618***	-0.618***	-0.660***	-0.275	-1.099***	-0.740***
	(0.114)	(0.121)	(0.118)	(0.163)	(0.162)	(0.192)	(0.286)	(0.226)
p-value $\beta_2 = -1$	0.253	0.0130	0.001	0.0210	0.0420	0.000	0.729	0.253
Observations	3590	2487	2415	3590	3590	3590	3590	1823

Standard errors in parentheses; 1000 bootstrap replications for median regression; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Table shows the coefficient for pension wealth from a regression similar to Table 5.3 with the following modifications:
(1) using financial wealth as dependent variable, full sample, (2) using financial wealth as dependent variable, retired sample,
(3) using financial wealth as dependent variable, old sample, (4) controlling for received inheritances (binary and amount),
(5) controlling for partner's education and health status, (6) and (7) interacting all covariates with the high-education dummy
and (8) excluding countries with large occupational pensions

We check the robustness of our results in Table 5.4 (see Tables 5.A.2 and 5.A.3 for detailed results). In columns (1) to (3) we consider net financial wealth rather than total net worth and we include housing wealth among the control variables.[20]

[19] For both the samples of retirees and older males, the difference with the full sample estimates might be partly driven by cohort effects, although these are likely small given our age restriction in the full sample (55-75 years old).

[20] We have carried out our estimations including other forms of non–financial wealth as well as not

The reason for doing so is that, according to Hurd et al. (2012), real wealth is mostly illiquid and its accumulation is likely to be driven by motives other than retirement planning. Housing in particular may be a consumption rather than an investment good, and as such affect the displacement effect. When we use financial wealth, for the full sample we cannot reject the hypothesis of full displacement using median regression. This result is in contrast with the findings of Gale (1998), according to which the offset is larger when using broader measures of wealth. For the sample of retirees, we find that for financial wealth the displacement effect is significantly different from zero, while for net worth this was true only using robust regression. Using the reasoning of Section 5.2.1, as $\sigma_{\eta_1\eta_2} \approx 0$, these estimates may be interpreted as lower bounds for the true offset, and hence we reject the hypothesis of no displacement. As expected, the offset for the old sample is very similar in magnitude to that estimated for the sample of retirees.

In the remaining robustness checks we focus only on the full sample because the results are qualitatively unchanged when we select the retirees or the old sample (they are available upon request from the authors). In columns (4) and (5) we add to our specification other explanatory variables that might be relevant in determining non–pension wealth. In particular, in column (4) we control for whether the individual has ever received inheritances or gifts worth more than €5,000 during his life and the total amount received. Indeed, for some individuals inheritances and monetary gifts might be an important component of non–pension wealth. Our results show that, although these variables are highly significant with the expected positive sign (see Tables 5.A.2 and 5.A.3), the estimated offset is still in the same range as before and significantly different from 0 and 100%. Column (5) shows that including controls for the education level and health status of the partner does not affect our main results. Changing the fixed parameters r and ρ to 2% (4%) does not affect the qualitative results (not reported); the estimated offset equals 23.6% (87.7%) using robust regressions, significantly different from zero at the 1% level.

As in Gale (1998) and Engelhardt and Kumar (2011), in columns (6) and (7) we

controlling for housing wealth. The results are virtually unchanged (they are available upon request from the authors).

interact all covariates with the high-education dummy, and report the estimated displacement effect for the high- and low educated groups[21]. We find that the offset is not significantly different from 100% for the highly educated, while the displacement effect is substantially lower in absolute value terms and not significantly different from zero offset for the less-educated sample. This result can be explained by the fact that individuals with higher education are more likely to be financially literate and to plan for retirement, while less educated individuals are more likely to procrastinate (see e.g. Laibson (1998)).

Finally, in column (8) we exclude those countries for which occupational pensions are typically a substantial share of pension income for retirees: Germany, Sweden, Denmark, the Netherlands and Belgium. In these countries, pensions may be seen as a form of private wealth, causing wrong inference on the displacement effect. The estimated crowd-out is about 10 percentage points lower compared to our baseline result using robust regression, and 15 percentage points higher using median regression. Overall, the results do not seem to be driven by the type of pension system in a particular country. The results are also robust to leaving one country out at the time (not reported). Using robust regression, the estimated displacement effect ranges between 38.6% when The Netherlands is left out of the analysis, to 57.5% when leaving out Italy, all significantly different from zero at the 1% level.

[21] The hypothesis of equal slope coefficients across education groups cannot be rejected for median regression ($p = 0.326$) and is marginally rejected for robust regression ($p = 0.044$).

Figure 5.2. Displacement effect across country groups

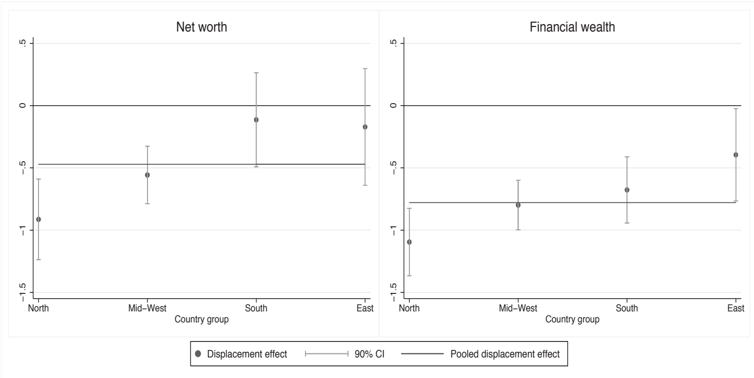


Figure 5.2 shows the displacement effect by country group[22], where North represents Sweden, Denmark and the Netherlands; Mid-West represents Austria, Germany, Switzerland, France and Belgium; South includes Spain, Italy and Greece and East represents Poland and Czech Republic. The estimates are obtained using robust regressions, and we plot 90% confidence intervals around the point estimates. In the Northern countries the extent of displacement of net worth is the highest (91%), and crowd-out is least in the South (11%), although the confidence intervals are wide. The pattern is similar when looking at financial wealth, although the offset is the lowest in the Eastern countries. More generous welfare systems (including social security) in the Northern countries could reduce the need to save for other reasons than retirement, such as precautionary savings. Also, more developed capital markets are likely to relax liquidity constraints. For these reasons, the displacement effect could be higher in the Northern countries compared to the Southern or Eastern European countries.

Another explanation of these findings can be found in the cross-country studies on Financial Literacy around the World[23] (Lusardi and Mitchell, 2011). These "FLat World" studies investigate responses to three comparable financial literacy questions in country-specific socio-economic surveys, focusing on the concepts of interest rates, inflation and risk diversification. The results show that the Nether-

[22] The sample sizes are too small to consider country-specific analysis.
[23] See the special issue of the Journal of Pension Economics and Finance, Volume 10, Issue 4 (2011).

lands (Alessie et al., 2011b) and Sweden (Almenberg and Säve-Söderbergh, 2011) score relatively well with 46.2% and 26.7% of respondents aged 25-65 answering all three questions correctly[24]. In Germany 56.8% of the sample provides three correct answers (Bucher-Koenen and Lusardi, 2011). In Italy, 28.3% answers all correctly (Fornero and Monticone, 2011), while in Russia[25] only 3.4% answers all correctly (Klapper and Panos, 2011). Jappelli (2010) conducts a panel data study using data from the International Institute for Management Development's World Competitiveness Yearbook (IMD-WCY). Jappelli finds a positive relationship between a country's GDP per capita and its economic literacy[26] using fixed-effects regressions, as well as the highest literacy scores in Denmark, Switzerland, the Netherlands and Sweden and the lowest scores in Poland, Italy and Spain. The evidence presented is certainly not exhaustive, but still seems to suggest more literate households in the Northern or Western countries, and less literacy in the Southern or Eastern countries, consistent with our results given the strong correlation between financial literacy and planning for retirement found in these same studies. Still, our cross-country results should be treated with caution, as the confidence intervals are wide, and, in fact, the group-specific estimates are never significantly different from the pooled displacement effect.

Overall, our results show that there is heterogeneity in the estimated offset across different groups of the population. However, the displacement effect is almost always significantly different from zero, indicating some degree of crowding out of private savings by pensions.

[24] The interest rate question in Sweden was considerably more difficult compared to the other countries; the percentage of no question correct is around 10% as in the Netherlands and Germany.

[25] We should be cautious with comparing the Russian results. First, the Czech Republic and Poland might well score differently compared to Russia. Second, the question on inflation literacy in Russia is framed differently from the other studies but is contentwise similar, while the risk diversification question asks Russians to rate the risks of different portfolio, and the remaining countries to give a true/false answer, which may bias the results against the Russians. Also, the answer category "Refuse to answer" was missing in all Russian questions.

[26] The literacy scores in the IMD-WCY are obtained by asking business leaders's and country experts's opinions on economic literacy in the population, instead of using household surveys as done in the "FLat World" studies.

5.4.1 The endogeneity of pension wealth

Although we have suggested an approach to limit the effect of measurement error, our results might still be biased due to the presence of unobserved heterogeneity. For example, taste for saving is likely to influence both pension wealth and private savings. Since both the dependent and the endogenous right-hand-side variable are positively affected by the unobserved taste for saving, the estimates of the displacement effect that we have obtained so far are likely to be attenuated. Therefore, we can still conclude that there is crowding out but its magnitude might be underestimated.

We try to overcome this endogeneity problem by using an instrumental variable identification strategy, which at the same time should reduce the impact of measurement error. We construct an instrument in the same spirit of that of Engelhardt and Kumar (2011), exploiting institutional differences across countries and groups of individuals. First, we compute median[27] pension benefits by country and employment sector (employee, civil servant and self-employed), relying on the information from the second wave of SHARE. Second, for each individual we calculate a "potential" pension wealth variable, using the relevant median benefit and the statutory retirement age that was in place at the time of retirement. Therefore, there are three sources of variation in our instrument: the country of residence, the sector of employment and the legal retirement age in place when leaving employment. For the validity of the instrument, we need to assume that, conditional on demographic characteristics, education, wealth and the country of residence, workers do not sort across employment sectors based on the taste for saving which is included in the error term. This assumption is similar to that made by Attanasio and Brugiavini (2003) and Engelhardt and Kumar (2011). Note that the instrument does not depend on any other individual characteristics which could be correlated with unobserved heterogeneity. We report results for our instrumental variables estimation in Table 5.5 (see Table 5.A.4 for the detailed results). There are two cautionary notes to bear in mind. First, we only present the results of IV quantile regression because the theory for IV robust regression is non–standard and we have not yet

[27] Using average pension income by country and employment sector gives similar results, available upon request.

Table 5.5. IV Median regression estimates

Variable	(1) Full sample	(2) Retired sample	(3) Old sample
Pension Wealth	-1.232	-0.622	-0.955
	(0.876)	(0.863)	(0.813)
p-value $\beta_2 = -1$	0.804	0.684	0.960
F-statistic first stage	41.895	31.232	38.567
Observations	3590	2487	2415

Bootstrapped standard errors in parentheses; 1000 replications. Table shows the coefficient for pension wealth from an Instrumental Variable median regression, instrumenting pension wealth. See the text for details on the instrument.

found a way to apply it to our context. Second, we employ the identification strategy of Chernozhukov and Hansen (2005), which provides consistent but imprecise estimates, a fact that has been noted by Chernozhukov and Hansen (2008) and Engelhardt and Kumar (2011) as well. Therefore, although we focus only on the point estimates and not on the confidence intervals, the point estimates should be interpreted with caution.

As expected, the estimated displacement effect is higher when correcting for the attenuation biases from endogeneity and measurement error, both if we focus on the full sample and if we consider only the retirees or the old sample. The partial F-statistic of the first stage (OLS) regression exceeds the "weak" instrument threshold of 10. The point estimates suggest full displacement, although the large standard errors yield insignificant results for pension wealth.

5.5 Conclusion

In this paper, we use SHARE data to come up with new estimates of the displacement effect of pensions on household wealth. The third wave of this survey, known as SHARELIFE, collects retrospective data on lifetime earnings, which can be linked to data on household wealth and subjective data on the expected replacement rate and retirement age collected in previous waves. Consequently, we are able to approximate in a convincing way the main variables needed to estimate the extent of crowding out between pension wealth and private wealth. In particular, we can compute both the present value of past and future income and pension wealth. According to our robust (median) regression results, each euro of pension wealth is associated with a 47 (61) cent decline in non–pension wealth. However, these results should be interpreted with caution: although we suggest an approach to limit the effects of correlated measurement errors in lifetime earnings and pension wealth, our estimates could still be biased and the direction of the bias is unclear. As Gale (1998, p. 720) stated, *"pension wealth data are of generally poor quality; all methods of calculating pension wealth in defined benefit plans are likely to create measurement error"*. For this reason, we estimate our model also on a sample of retirees and older households, for whom the information on lifetime earnings and pension wealth comes from two different sources. For this group measurement error, although present, is likely to be uncorrelated and the direction of the bias in our preferred specification is thus clear: parameter estimates are attenuated and, therefore, they can provide lower bounds to the true offset. We find that the lower bounds for the crowd–out are significantly different from zero and they range between 17% and 30%, depending on the estimation method.

We also find that the extent of the crowding out effect differs across education groups: for the low educated, we do not find any evidence of displacement whereas for the high educated pension wealth completely crowds out private wealth. Moreover, the level of displacement is limited in the Mediterranean and Eastern European countries. The IV estimates, instrumenting pension wealth to account for omitted variable bias, suggest full displacement although estimated with less precision.

Our results shed light on the impact of recent and future pension reforms in Europe. The main results suggest that European households will react to reductions in pensions by increasing private savings, although not strong enough to smooth consumption over the life–cycle. Government policy should focus especially on the less-educated and perhaps financially illiterate households, for which we have shown limited displacement.

Although we have suggested strategies to address the issues of measurement error and unobserved heterogeneity, more work needs to be done. Most notably, future waves of SHARE can be used to construct a panel data set, with which unobservable household characteristics as well as the choice of retirement date can be addressed.

5.A Detailed estimation results

Table 5.A.1. Full table estimation results

	Robust regression			Median regression		
Variables	(1) Full sample	(2) Retired sample	(3) Old sample	(4) Full sample	(5) Retired sample	(6) Old sample
Pension wealth	-0.471***	-0.205**	-0.173*	-0.609***	-0.296	-0.306*
	(0.0878)	(0.0936)	(0.0965)	(0.151)	(0.180)	(0.177)
Age 55-60	-1.406***	-0.538**		-1.409***	-0.359	
	(0.155)	(0.207)		(0.173)	(0.226)	
Age 70-75	1.797***	1.483***	1.674***	1.614***	1.347***	1.505***
	(0.172)	(0.161)	(0.167)	(0.177)	(0.175)	(0.187)
Second earner	0.128	0.230	0.206	0.175	0.189	0.270
	(0.151)	(0.159)	(0.171)	(0.167)	(0.191)	(0.188)
Married	0.403*	0.148	0.173	0.332	-0.0066	-0.070
	(0.233)	(0.247)	(0.267)	(0.275)	(0.292)	(0.304)
No children	0.355	0.170	0.503	0.469*	0.0579	0.564
	(0.254)	(0.262)	(0.289)	(0.282)	(0.274)	(0.293)
High educated	0.0854	0.229	0.100	-0.0755	0.177	0.133
	(0.175)	(0.200)	(0.202)	(0.197)	(0.233)	(0.234)
Medium educated	0.255	0.229	0.362	0.139	0.233	0.340
	(0.163)	(0.186)	(0.195)	(0.175)	(0.205)	(0.211)
Bad health	0.120	0.0175	0.179	0.0712	0.0674	0.167
	(0.149)	(0.152)	(0.170)	(0.143)	(0.165)	(0.163)
Gaps in career	-0.824***	-0.109	-0.236	-0.756***	-0.174	-0.275
	(0.146)	(0.180)	(0.183)	(0.164)	(0.208)	(0.211)
Sweden	-0.820***	-0.882**	-0.880***	-0.992**	-1.104**	-1.382***
	(0.287)	(0.341)	(0.328)	(0.412)	(0.495)	(0.459)
Denmark	-0.311	-0.743**	-0.716**	-0.457	-0.831*	-1.020**
	(0.286)	(0.321)	(0.330)	(0.369)	(0.458)	(0.428)
Netherlands	0.528*	0.467	0.590*	0.521	0.365	0.481
	(0.285)	(0.322)	(0.333)	(0.336)	(0.356)	(0.346)
Belgium	1.397***	1.172***	1.446***	1.522***	1.244***	1.590***
	(0.279)	(0.300)	(0.316)	(0.356)	(0.408)	(0.377)
France	0.755**	0.295	0.413	0.337	-0.270	-0.267
	(0.312)	(0.340)	(0.389)	(0.463)	(0.510)	(0.629)
Switzerland	-5.575***	-4.633***	-4.734***	-5.595***	-4.275***	-5.045***
	(0.324)	(0.389)	(0.370)	(0.589)	(0.741)	(0.628)
Austria	0.628	0.362	0.245	0.743	0.213	0.197
	(0.389)	(0.409)	(0.442)	(0.477)	(0.507)	(0.549)
Spain	1.649***	1.825***	1.763***	1.314**	1.544**	1.504**
	(0.371)	(0.397)	(0.437)	(0.506)	(0.599)	(0.585)
Italy	2.477***	2.237***	2.563***	2.325***	2.171***	2.431***
	(0.274)	(0.293)	(0.315)	(0.302)	(0.350)	(0.352)
Greece	2.053***	1.802***	2.100***	1.950***	1.401*	1.345*
	(0.400)	(0.465)	(0.490)	(0.742)	(0.747)	(0.745)
Poland	3.027***	2.563***	2.608***	2.985***	2.355***	2.469***
	(0.377)	(0.408)	(0.472)	(0.330)	(0.340)	(0.363)
Czech Republic	2.201***	1.979***	2.171***	2.102***	1.920***	2.055***
	(0.305)	(0.322)	(0.339)	(0.286)	(0.311)	(0.294)
Constant	-4.786***	-4.664***	-5.128***	-4.385***	-4.244***	-4.559***
	(0.329)	(0.358)	(0.372)	(0.374)	(0.427)	(0.418)
Observations	3590	2487	2415	3590	2487	2415
p-value $\beta_2 = -1$	0.000	0.000	0.000	0.011	0.000	0.000
p-value Country effects	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Bootstrapped standard errors for median regression, 1000 replications

Table 5.A.2. Full estimation results robustness checks, robust regression

Variables	(1) Financial wealth, full	(2) Financial wealth, retired	(3) Financial wealth, old	(4) Inheritances received	(5) Partner's characteristics	(6) Low educated	(7) High educated	(8) No occupational pensions
Pension wealth	-0.778***	-0.614***	-0.532***	-0.527***	-0.488***	-0.215*	-0.833***	-0.380***
	(0.0738)	(0.0734)	(0.0779)	(0.0877)	(0.0876)	(0.122)	(0.153)	(0.121)
Age 55-60	-1.508***	-0.653***		-1.421***	-1.424***	-1.340***	-1.537***	-1.397***
	(0.127)	(0.159)		(0.154)	(0.155)	(0.178)	(0.293)	(0.204)
Age 70-75	1.898***	1.579***	1.784***	1.820***	1.812***	1.733***	1.862***	1.390***
	(0.144)	(0.125)	(0.135)	(0.171)	(0.172)	(0.206)	(0.341)	(0.240)
Second earner	-0.142	-0.0818	-0.0961	0.0777	-0.117	0.183	0.151	0.215
	(0.123)	(0.123)	(0.137)	(0.149)	(0.168)	(0.175)	(0.280)	(0.203)
Married	0.0023	-0.117	-0.153	0.412*	0.255	0.276	0.558	0.143
	(0.190)	(0.191)	(0.211)	(0.230)	(0.242)	(0.271)	(0.427)	(0.331)
No children	0.355*	0.239	0.394*	0.331	0.377	0.346	0.0912	0.268
	(0.204)	(0.205)	(0.233)	(0.251)	(0.252)	(0.290)	(0.489)	(0.345)
High educated	-0.677***	-0.397***	-0.557***	-0.0405	-0.0662			0.108
	(0.142)	(0.146)	(0.162)	(0.174)	(0.183)			(0.243)
Medium educated	0.0527	0.0511	0.134	0.201	0.159			0.152
	(0.136)	(0.137)	(0.156)	(0.161)	(0.165)			(0.221)
Bad health	0.279**	0.180	0.292**	0.197	0.153	0.148	0.0378	0.287
	(0.123)	(0.116)	(0.133)	(0.148)	(0.150)	(0.169)	(0.327)	(0.194)
Gaps in career	-0.810***	0.0087	-0.234	-0.826***	-0.835***	-0.654***	-1.109***	-0.865***
	(0.123)	(0.138)	(0.149)	(0.145)	(0.145)	(0.174)	(0.270)	(0.204)
Sweden	-0.637***	-0.451*	-0.749***	-0.824***	-0.787***	-1.356***	-0.0327	
	(0.237)	(0.257)	(0.260)	(0.290)	(0.289)	(0.364)	(0.522)	
Denmark	-0.243	-0.646**	-0.725***	-0.254	-0.320	-0.395	-0.206	
	(0.237)	(0.249)	(0.263)	(0.284)	(0.286)	(0.364)	(0.455)	
Netherlands	0.520**	0.396	0.431	0.600**	0.604**	0.217	0.819*	
	(0.239)	(0.259)	(0.275)	(0.282)	(0.288)	(0.363)	(0.473)	
Belgium	0.868***	0.817***	0.871***	1.430***	1.431***	1.148***	1.626***	
	(0.229)	(0.230)	(0.253)	(0.274)	(0.279)	(0.348)	(0.435)	
France	-0.223	-0.720***	-0.461	0.830***	0.818***	0.829**	0.0730	
	(0.259)	(0.266)	(0.318)	(0.307)	(0.312)	(0.381)	(0.552)	
Switzerland	-5.555***	-4.195***	-4.753***	-5.695***	-5.517***	-6.236***	-4.760***	-6.393***
	(0.274)	(0.309)	(0.313)	(0.326)	(0.324)	(0.406)	(0.518)	(0.356)
Austria	0.767**	0.771**	0.560	0.786**	0.720*	0.156	1.537**	-0.0631
	(0.318)	(0.318)	(0.353)	(0.383)	(0.388)	(0.487)	(0.648)	(0.398)
Spain	0.257	0.340	0.211	1.807***	1.739***	1.219***	3.225***	0.940**
	(0.295)	(0.299)	(0.327)	(0.366)	(0.369)	(0.415)	(0.955)	(0.375)
Italy	1.557***	1.397***	1.572***	2.565***	2.551***	2.165***	3.039***	1.765***
	(0.225)	(0.225)	(0.225)	(0.270)	(0.276)	(0.316)	(0.698)	(0.291)
Greece	1.707***	1.447***	1.639***	1.987***	2.018***	1.637***	2.482***	1.343***
	(0.328)	(0.358)	(0.392)	(0.396)	(0.401)	(0.486)	(0.703)	(0.398)
Poland	3.735***	3.107***	3.087***	3.185***	3.044***	3.000***	2.922***	2.299***
	(0.312)	(0.318)	(0.380)	(0.373)	(0.377)	(0.457)	(0.712)	(0.401)
Czech Republic	2.459***	2.161***	2.267***	2.296***	2.240***	2.021***	2.249***	1.470***
	(0.248)	(0.249)	(0.271)	(0.300)	(0.305)	(0.367)	(0.585)	(0.336)
Constant	-5.233***	-5.083***	-5.364***	-4.964***	-4.518***	-4.679***	-4.420***	-3.890***
	(0.274)	(0.279)	(0.297)	(0.328)	(0.372)	(0.396)	(0.514)	(0.436)
Housing wealth	-0.0035	-0.0043	-0.0450**					
	(0.0091)	(0.0081)	(0.0179)					
Received inheritance				0.522***				
				(0.146)				
Amount inherited				0.669***				
				(0.143)				
High educated spouse					0.458**			
					(0.215)			
Medium educated spouse					0.397**			
					(0.179)			
Bad health spouse					-0.223			
					(0.157)			
Observations	3590	2487	2415	3590	3590	3590	3590	1823
p-value $\beta_2 = -1$	0.003	0.000	0.000	0.000	0.000	0.000	0.277	0.000
p-value Country effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

See Table 5.4. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
In column (8), France is used as the baseline country.

Table 5.A.3. Full estimation results robustness checks, median regression

Variables	(1) Financial wealth, full	(2) Financial wealth, retired	(3) Financial wealth, old	(4) Inheritances received	(5) Partner's characteristics	(6) Low educated	(7) High educated	(8) No occupational pensions
Pension wealth	-0.870***	-0.692***	-0.618***	-0.618***	-0.660***	-0.275	-1.099***	-0.740***
	(0.114)	(0.121)	(0.118)	(0.163)	(0.162)	(0.192)	(0.286)	(0.226)
Age 55-60	-1.477***	-0.433***		-1.399***	-1.483***	-1.238***	-1.943***	-1.390***
	(0.154)	(0.163)		(0.170)	(0.184)	(0.196)	(0.404)	(0.217)
Age 70-75	1.948***	1.776***	1.891***	1.674***	1.629***	1.550***	1.652***	1.207***
	(0.143)	(0.132)	(0.138)	(0.177)	(0.186)	(0.209)	(0.437)	(0.216)
Second earner	-0.143	-0.144	-0.0901	0.119	-0.102	0.165	0.258	0.423**
	(0.145)	(0.145)	(0.162)	(0.167)	(0.184)	(0.185)	(0.406)	(0.211)
Married	-0.128	-0.110	-0.194	0.348	0.190	0.182	0.524	-0.178
	(0.203)	(0.196)	(0.215)	(0.253)	(0.281)	(0.286)	(0.673)	(0.378)
No children	0.226	0.216	0.267	0.290	0.522*	0.407	0.179	0.180
	(0.222)	(0.197)	(0.197)	(0.249)	(0.290)	(0.277)	(0.617)	(0.347)
High educated	-0.818***	-0.604***	-0.717***	-0.182	-0.267			0.0925
	(0.171)	(0.174)	(0.198)	(0.206)	(0.204)			(0.263)
Medium educated	-0.0997	-0.0322	0.0255	0.131	0.0844			0.0550
	(0.141)	(0.136)	(0.150)	(0.168)	(0.177)			(0.214)
Bad health	0.206	0.167	0.231	0.134	0.102	0.140	-0.262	0.163
	(0.126)	(0.119)	(0.140)	(0.136)	(0.145)	(0.169)	(0.391)	(0.180)
Gaps in career	-0.796***	-0.0446	-0.237	-0.796***	-0.780***	-0.617***	-0.982**	-0.742***
	(0.143)	(0.136)	(0.162)	(0.168)	(0.175)	(0.185)	(0.384)	(0.210)
Sweden	-1.376***	-1.255***	-1.596***	-0.947**	-1.077**	-1.700***	-0.326	
	(0.299)	(0.385)	(0.352)	(0.396)	(0.413)	(0.472)	(0.683)	
Denmark	-0.476*	-0.722**	-0.945***	-0.352	-0.490	-0.429	-0.646	
	(0.254)	(0.341)	(0.326)	(0.357)	(0.370)	(0.433)	(0.626)	
Netherlands	0.531**	0.373	0.412	0.693**	0.592*	0.349	0.904	
	(0.230)	(0.280)	(0.256)	(0.314)	(0.320)	(0.373)	(0.577)	
Belgium	0.815***	0.788***	0.843***	1.537***	1.543***	1.576***	1.174*	
	(0.234)	(0.269)	(0.272)	(0.374)	(0.395)	(0.407)	(0.619)	
France	-0.991**	-1.484***	-1.453***	0.399	0.462	0.515	-0.240	
	(0.416)	(0.511)	(0.613)	(0.408)	(0.456)	(0.438)	(1.000)	
Switzerland	-6.319***	-4.428***	-5.137***	-5.800***	-5.586***	-6.190***	-5.061***	-5.889***
	(0.537)	(0.455)	(0.648)	(0.595)	(0.603)	(0.766)	(1.012)	(0.650)
Austria	0.593	0.303	0.0036	0.944**	0.790	0.519	1.455	0.367
	(0.492)	(0.526)	(0.495)	(0.418)	(0.480)	(0.527)	(0.938)	(0.581)
Spain	-0.215	-0.0919	-0.127	1.587***	1.430**	1.065*	2.303	1.093*
	(0.400)	(0.406)	(0.413)	(0.514)	(0.581)	(0.596)	(1.522)	(0.586)
Italy	1.677***	1.501***	1.698***	2.487***	2.406***	2.122***	2.754***	2.062***
	(0.227)	(0.222)	(0.228)	(0.297)	(0.328)	(0.341)	(0.803)	(0.401)
Greece	0.935*	0.858*	0.886*	1.503**	1.864**	1.343*	2.703*	1.354*
	(0.506)	(0.486)	(0.475)	(0.726)	(0.772)	(0.804)	(1.578)	(0.692)
Poland	3.615***	2.954***	3.083***	3.188***	2.949***	2.973***	2.711***	2.480***
	(0.260)	(0.248)	(0.288)	(0.333)	(0.342)	(0.363)	(0.696)	(0.435)
Czech Republic	2.284***	2.163***	2.201***	2.291***	2.096***	2.141***	1.728***	1.667***
	(0.217)	(0.213)	(0.217)	(0.293)	(0.296)	(0.335)	(0.619)	(0.520)
Constant	-4.669***	-4.797***	-4.945***	-4.691***	-3.992***	-4.507***	-3.681***	-3.528***
	(0.286)	(0.309)	(0.283)	(0.383)	(0.432)	(0.442)	(0.860)	(0.586)
Housing wealth	-0.0057	-0.0025	-0.0425					
	(0.0240)	(0.0285)	(0.0342)					
Received inheritance				0.589***				
				(0.177)				
Amount inherited				0.753**				
				(0.300)				
High educated spouse					0.619**			
					(0.279)			
Medium educated spouse					0.284			
					(0.192)			
Bad health spouse					-0.295*			
					(0.170)			
Observations	3590	2487	2415	3590	3590	3590	3590	1823
p-value $\beta_2 = -1$	0.253	0.0130	0.001	0.0210	0.0420	0.000	0.729	0.253
p-value Country effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

See Table 5.4. Bootstrapped standard errors in parentheses, 1000 replications; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
In column (8), France is used as the baseline country.

Table 5.A.4. IV Quantile regression estimates

Variable	(1) Full sample	(2) Retired sample	(3) Old sample
Pension Wealth	-1.232	-0.622	-0.955
	(0.876)	(0.863)	(0.813)
Age 55-60	-0.144***	-0.044	
	(0.022)	(0.027)	
Age 70-75	0.179***	0.136***	0.172***
	(0.038)	(0.035)	(0.038)
Second earner	0.012	0.017	0.026
	(0.019)	(0.020)	(0.021)
Married	0.037	0.006	0.003
	(0.031)	(0.034)	(0.035)
No children	0.050*	-0.001	0.054*
	(0.027)	(0.029)	(0.031)
High educated	0.014	0.031	0.029
	(0.040)	(0.045)	(0.043)
Medium educated	0.030	0.029	0.045
	(0.026)	(0.026)	(0.028)
Bad Health	0.005	0.001	0.014
	(0.016)	(0.017)	(0.018)
Gaps in career	-0.082***	-0.021	-0.036
	(0.024)	(0.025)	(0.028)
Civil servant	0.038	0.031	0.024
	(0.033)	(0.030)	(0.035)
Employee	-0.022	-0.016	-0.037
	(0.028)	(0.029)	(0.032)
Sweden	-0.099**	-0.115**	-0.111**
	(0.040)	(0.046)	(0.045)
Netherlands	0.049	0.029	0.067*
	(0.032)	(0.038)	(0.036)
Austria	0.075	0.016	0.019
	(0.051)	(0.054)	(0.058)
Switzerland	-0.521***	-0.425***	-0.435***
	(0.094)	(0.114)	(0.099)
Spain	0.141***	0.151**	0.156***
	(0.051)	(0.059)	(0.058)
Italy	0.225***	0.207***	0.239***
	(0.035)	(0.038)	(0.037)
France	0.037	-0.020	-0.001
	(0.050)	(0.063)	(0.072)
Denmark	-0.077	-0.109*	-0.124**
	(0.056)	(0.058)	(0.053)
Belgium	0.149***	0.130***	0.182***
	(0.034)	(0.043)	(0.042)
Greece	0.173***	0.125*	0.135*
	(0.066)	(0.072)	(0.073)
Czech Republic	0.161**	0.162**	0.156**
	(0.079)	(0.073)	(0.071)
Poland	0.226***	0.187**	0.198***
	(0.084)	(0.076)	(0.076)
Constant	-0.366***	-0.381***	-0.382***
	(0.110)	(0.100)	(0.097)
Observations	3590	2487	2415
p-value $\beta_2 = -1$	0.804	0.684	0.960
p-value Country effects	0.000	0.000	0.000
F-statistic first stage	41.895	31.232	38.567
p-value first stage	0.000	0.000	0.000

See Table 5.5. Bootstrapped standard errors in parentheses; 1000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Dependent and endogenous RHS variable divided by 10

5.B Advantages of retrospective information

In this appendix, we discuss the advantage of retrospective earnings information compared to the traditional approach, used by, amongst others, Gale (1998). Our main interest is in estimating the parameter β_2, the displacement effect, in the regression equation

$$A = z_1\beta_1 + z_2\beta_2 + \boldsymbol{x}'\gamma + \varepsilon$$

where A denotes private wealth, z_1 permanent income, z_2 pension wealth and $\boldsymbol{x}'$ a vector of controls. Using retrospective earnings data from SHARELIFE, z_1 is a one-dimensional measure of lifetime income, measured with error. Using the approach of Gale (1998), $z_1\beta_1$ is replaced by $\boldsymbol{g}_1'\delta_1$, where $\boldsymbol{g}_1'$ is a vector of variables proxying lifetime income, consisting of education, age, current income, marital status and the expected age of retirement. Hence, $\boldsymbol{g}_1'$ is a multi-dimensional measure of lifetime income, again measured with error. The economic model presented in Section 2 provides a value for $\beta_1 = 1$, which we can use to estimate a restricted model, such that we can sign the direction of the bias in the estimated displacement effect. Instead, economic theory does not provide any intuition regarding the magnitude of the elements in δ_1, and hence a restricted estimator is not feasible.

The SHARE survey contains enough information to estimate Gale's model on the sample of non-retirees.[28] An important impedient to this approach is that SHARE asks individuals to report an expected replacement rate of pension benefits. Expected pension benefits can then simply be computed by multiplying this replacement rate by current income. In contrast, the Survey of Consumer Finances (SCF) used by Gale asks respondents to provide an expected money amount of pension benefits.[29] This difference in survey questions has important consequences for estimating Gale (1998)'s model: using SHARE data, pension wealth is a linear

[28] Note that the approach of Gale (1998) is not suitable for the sample of retirees, as current labour income is not observed for this sample, except for the case where individuals are followed repeatedly over time and retire in the period surveyed. Gale indeed estimates his model for the sample of non-retirees.

[29] Given the different institutions between countries in Europe, we believe that the replacement rate is indeed the appropriate pension income measure to elicit in a multi-country survey. The money amount may be more appropriate in a single-country survey, although in, for instance, The Netherlands and Italy, the replacement rate is the construct alluded to in political and popular debate.

function of current income, and hence the measurement error in pension wealth correlates with the measurement error in g_1. Using the SCF, one may reasonably argue that the measurement errors in g_1 and z_2 are uncorrelated. The derivation of Section 2.1 clearly shows that this correlation biases the coefficients further away from the true values.

Table 5.B.1 shows the results of estimating Gale (1998)'s model using SHARE data, without using any retrospective earnings information, for the sample of non-retirees. In column (I), we proxy permanent income with Age, monthly real income (in €000's), education, marital status, a dummy for a second earner in the household, and the expected age of retirement. In column (II), we additionally include interactions between age and income as well as education and income.

Table 5.B.1 shows that the estimated displacement effect is positive and not significantly different from zero using Gale (1998)'s approach with SHARE data. The bias towards zero, compared to the model's prediction, is most likely driven by correlated measurement errors between pension wealth and current income, as predicted in Section 2.1 (see equation 14). In column (II), the marginal effect of income for a 60-year old, high educated respondent equals 0.43, significantly different from zero (p=0.004), which is comparable to the effect of income in column (I). We conclude that one cannot use SHARE data to estimate the displacement effect, due to the presence of measurement errors. The approach we suggest in this paper, combining economic theory with retrospective earnings information, does allow for the identification of the displacement effect.

Table 5.B.1. Gale's regression

Variables	(1) Gale's model	(2) Gale's model with interactions
Pension wealth	0.150	0.135
	(0.132)	(0.133)
Monthly income	0.420***	-0.655
	(0.0730)	(1.366)
Age	0.0215	-0.00588
	(0.0268)	(0.0510)
High educated	0.836***	0.503
	(0.196)	(0.368)
Medium educated	0.389**	-0.251
	(0.169)	(0.363)
Age x Income		0.0143
		(0.0240)
High educated x Income		0.224
		(0.156)
Medium educated x Income		0.389*
		(0.183)
Married	0.965***	0.943***
	(0.262)	(0.253)
No children	0.0251	-0.00680
	(0.275)	(0.258)
Bad health	-0.211	-0.202
	(0.179)	(0.178)
Second earner	-0.101	-0.0874
	(0.177)	(0.172)
Expected retirement age	-0.00293	-0.00203
	(0.0298)	(0.0300)
Sweden	0.115	0.119
	(0.278)	(0.276)
Denmark	0.852***	0.849**
	(0.294)	(0.290)
Netherlands	0.193	0.188
	(0.293)	(0.294)
Belgium	1.109***	1.090***
	(0.295)	(0.289)
France	0.756**	0.715*
	(0.345)	(0.353)
Switzerland	-0.0716	-0.0848
	(0.326)	(0.322)
Austria	0.584	0.579
	(0.455)	(0.453)
Spain	1.350***	1.366***
	(0.371)	(0.373)
Italy	0.418	0.355
	(0.347)	(0.343)
Greece	0.376	0.385
	(0.375)	(0.368)
Poland	-0.827*	-0.823*
	(0.419)	(0.408)
Czech Republic	-0.258	-0.340
	(0.334)	(0.336)
Constant	-1.043	0.901
	(2.279)	(3.081)
Observations	1022	1022
p-value g_1	0.000	0.000
p-value Country effects	0.000	0.002

Robust regression estimates. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

g_1: Age, Income, Expected retirement age, Education, Age×Income, Education×Income

Chapter 6

Samenvatting

Inkomsten uit pensioenen beslaan een groot deel van de totale inkomsten die een gemiddeld persoon over zijn of haar levensduur genereert. Voor het merendeel van de bevolking zijn verwachte pensioeninkomens het grootste vermogensbestanddeel. Dit verklaart voor een groot deel de hoeveelheid literatuur die over dit onderwerp is verschenen. Immers, zonder inkomsten uit pensioenen zouden we ofwel langer, tot het einde van ons leven doorwerken, ofwel meer sparen om op een gegeven moment te kunnen stoppen met werken. In dit proefschrift ga ik in op dit laatste effect, en bestudeer de spaarreactie van huishoudens op pensioeninkomsten. De hoofdvraag die ik probeer beantwoorden is dan ook: *Is er een spaarreactie van huishoudens op pensioenen?*

Economische theorie is relatief eenduidig over het antwoord op deze vraag: Uiteraard gedragen huishoudens zich anders in een scenario zonder pensioenen als in een scenario met pensioenen. Hieraan ligt ten grondslag dat mensen vooruit denken: gegeven dat ik een pensioen ontvang als ik stop met werken hoef ik nu minder te sparen om rond te kunnen komen. Recente (en minder recente) ontwikkelingen maken dit gegeven echter minder waarschijnlijk. De vergrijzing zorgt voor een toename van het aantal gepensioneerden ten opzichte van het aantal werknemers, en zal ofwel leiden tot een toename van de premiedruk voor jongeren of een verlaging van de AOW-uitkering voor ouderen, of een combinatie hiervan. Met de kennis van nu is de keuze voor een omslagstelsel voor de AOW bij de introductie hiervan in de jaren '50 een slechte geweest. Zolang ouderen mogen stemmen op kortzichtige politici zal hieraan echter weinig veranderen, met uitzondering van de traditionele kaasschaaf. Een andere ontwikkeling is de dekkingsgraad van pensioenfondsen. De financiële crisis toont aan dat het rendement van de tweede pijler van ons pensioenstelsel, gefinancierd door werkgevers en werknemers, onderhevig is aan resultaten behaald op de beurs. De omzetting van het huidige systeem, gebaseerd op uitkomsten, naar een systeem wat gebaseerd is op bijdrages, zal de risico's nog meer expliciet maken dan ze nu al zijn.

Het voorgaande pleit voor een aanpak waar de verwachtingen ten aanzien van toekomstig pensioeninkomen centraal staan. Consumptiegedrag onder onzekerheid is gebaseerd op de *verwachtingen* van huishoudens: als ik verwacht meer pensioen te krijgen, hoef ik nu minder geld opzij te leggen voor later, om mijn consumptie op peil te houden. Onzekerheid leidt typisch echter ook tot een voorzorgsmotief: ik weet niet zeker hoeveel pensioen ik later zal ontvangen. Hoe onzekerder ik ben over de hoogte van mijn pensioenuitkering, des te meer leg ik nu geld opzij om mogelijke tegenvallers te compenseren. Hoewel deze twee hypothesen plausibel zijn, en theoretisch goed gefundeerd, blijken ze in de praktijk lastig te toetsen. Tot voor kort was informatie met betrekking tot verwachtingen niet beschikbaar; in plaats daarvan veronderstellen economen rationele verwachtingen. In dit proefschrift maak ik gebruik van recent verzamelde verwachtingsdata: huishoudens worden gevraagd hun verwachtingen kenbaar te maken. In combinatie met data over spaargedrag kunnen we bovenstaande hypothesen toetsen.

In hoofdstuk 2, geschreven met Rob Alessie en Adriaan Kalwij, bestudeer ik de kwaliteit van de antwoorden op verwachtingsvragen. Het type vraag dat gesteld wordt is *niet* in de vorm: “Vertelt u eens hoeveel pensioeninkomen u verwacht?” In plaats daarvan wordt de methodologie van Dominitz en Manski gebruikt, toegepast op de vervangingsratio (de ratio van pensioeninkomen ten opzichte van huidig inkomen): “Wat is volgens u de kans dat uw vervangingsratio lager is dan 100%?” Dezelfde vraag wordt herhaald voor de kansen op een vervangingsratio lager dan 90%, 80%, 70%, 60% en 50%, alsook de kans op een vervangingsratio van meer dan 100%. Samen genomen geven de antwoorden op deze vragen een goed beeld van de kansverdeling van toekomstig pensioeninkomen. Deze kansverdeling stelt ons in staat om, voor elk huishouden apart, het gemiddelde en de standaarddeviatie uit te rekenen, als maatstaven voor de verwachting van en de onzekerheid over de hoogte van het toekomstig pensioeninkomen. De Nederlandse werknemer verwacht gemiddeld een pensioen van 75-80% van zijn huidig inkomen te ontvangen, met een standaarddeviatie van 15%. Oudere werknemers verwachten meer pensioeninkomen en zijn minder onzeker. Hoogopgeleiden verwachten een lager percentage van hun huidige inkomen te ontvangen, en tonen aan onzekerder te zijn. Sinds 2007 zijn huishoudens minder pensioeninkomen gaan verwachten, en zijn ze onzekerder geworden. Gegeven de situatie op de beurs zijn deze resultaten niet verassend, en dragen ze bij aan het vertrouwen wat onderzoekers mogen hebben in de verwachtingsdata.

Een belangrijke bevinding is echter dat niet alle huishoudens in staat zijn deze vragen te beantwoorden. Kansen zijn een ingewikkeld concept voor een groot deel van de respondenten. De serie antwoorden moet voldoen aan twee statistische eisen: monotoniciteit van de (cumulatieve) kansverdelingfunctie, en kansen moeten optellen tot maximaal 100%. Voor een derde deel van onze steekproef wordt niet aan beide eisen voldaan. Het berekenen van een gemiddelde en standaarddeviatie is voor deze groep lastig, zoniet onmogelijk. Niet verassend speelt genoten onderwijs een belangrijke rol: laagopgeleiden geven vaker statistisch inconsistente antwoorden dan hoogopgeleiden. Als gevolg daarvan bestaat de uiteindelijke dataset uit voornamelijk hoogopgeleiden, oftewel een selectieve steekproef. Gegeven bovenstaande bevindingen zorgt dit selectieproces voor een te hoge mate van pessimisme en teveel onzekerheid ten aanzien van pensioeninkomen, waarvoor onderzoekers een correctiemethode zullen moeten toepassen om uitspraken te kunnen doen over de hele populatie.

In hoofdstuk 3 toets ik de hypotheses dat een hoger verwacht pensioen leidt tot lagere besparingen, en dat meer onzekerheid leidt tot meer besparingen. Ik schat hiervoor een spaarvergelijking, afgeleid uit een theoretisch model, waar consumptie afhangt van inkomen, vermogen, levensverwachting en de verwachtingen ten aanzien van pensioeninkomen. Besparingen worden gemeten door voor elk huishouden te berekenen hoeveel het financiële vermogen toe- of afneemt tussen twee opeenvolgende jaren. Ik probeer zoveel mogelijk te corrigeren voor het feit dat de verwachtingsvragen leiden tot een aselecte steekproef, zoals aangetoond in hoofdstuk 2. Bovendien beantwoordt niet elk huishouden de (hele) vragenlijst twee jaar achter elkaar, waardoor we geen besparingen kunnen meten voor deze groep. Ook dit kan leiden tot een selectieve steekproef, waarvoor ik probeer te corrigeren. Ik gebruik een kwantielregressiemodel, waarin de spaarreactie afhangt van de positie van een huishouden ten opzichte van andere huishoudens in de verdeling van besparingen. Simpel gezegd vermoed ik dat huishoudens die weinig sparen zich anders gedragen dan huishoudens die veel geld opzij zetten. De motivatie volgt uit het feit dat banken niet toestaan dat het financiële vermogen van een huishouden (te sterk) negatief wordt. Uit het theoretische model volgt dat huishoudens met een lage spaarvoet minder sterk reageren op veranderingen in hun pensioeninkomen dan huishoudens met een hogere spaarvoet, typische de rijke, vermogende huishoudens. Meer in het algemeen geldt dat een deel van de bevolking weinig vooruitziend is, en zich dus anders gedraagt dan verondersteld in het theoretische model.

Ik vind dat alleen de huishoudens in de bovenste helft van de verdeling zich gedragen volgens het model: zij sparen meer als gevolg van lagere verwachte pensioeninkomsten en als gevolg van meer onzekerheid. Ook geldt dat deze groep meer spaargeld opzij zet als gevolg van een hogere levensverwachting. Dit in tegenstelling tot de minder vermogende huishoudens, die geen spaarreactie tonen ten aanzien van pensioeninkomen of levensverwachting. Deze resultaten zijn consistent met het theoretische model met een ondergrens aan financieel vermogen. Tot dusver is dit een van de eerste empirische studies naar het voorzorgsmotief voor spaargedrag. De unieke data ten aanzien van verwachtingen maken deze, zeker vandaag de dag relevante studie mogelijk.

In hoofdstuk 4, in samenwerking met Rob Alessie en Adriaan Kalwij, kijk ik naar andere vormen van private pensioenaanvullingen. In plaats van naar totale besparingen te kijken, zoals in hoofdstuk 3, focus ik hier op specifieke producten: lijfrentes, koopsompolissen en kapitaalverzekeringen. Het aanschaffen van een lijfrenteverzekering of koopsompolis resulteert in een extra aanvulling op het pensioen. Een kapitaalverzekering daarentegen keert typisch een bedrag ineens uit, en kan dus meer gezien worden als het definitief opzij zetten van een deel van het vermogen voor consumptie na uitkering. Onder voorwaarden zijn deze producten belastingtechnisch gezien aantrekkelijk.

Zowel lijfrenteverzekeringen als koopsompolissen zijn economisch zeer aantrekkelijke producten. Ze garanderen een periodieke aanvulling op het inkomen zolang de bezitter leeft. In een belangrijke studie heeft Yaari in 1965 aangetoond dat dit type producten theoretisch optimaal zijn. Sterker nog, iedereen zou al zijn geld in deze producten moeten steken. In de praktijk blijkt dit echter niet het geval, en deze observatie wordt typisch aangeduid met de 'Annuity puzzle'. Oorzaken voor dit contrast tussen theorie en realiteit zijn uitgebreid onderzocht, en wijzen op niet-realistische veronderstellingen in de studie van Yaari, de verzekeringen zijn te duur (denk aan woekerpolissen) of verschillen in de praktijk van hoe ze theoretisch vormgegeven zijn, altruïsme ten aanzien van het nageslacht, grote zorguitgaven in de laatste jaren van het leven en meer. In dit hoofdstuk proberen we in kaart te brengen wie deze producten wel kopen. De resultaten tonen aan dat de rijkere, vermogende en hoogopgeleide huishoudens met name dit type producten kopen. Een zelfde sociaaleconomische splitsing tussen bezitters en niet-bezitters geldt voor de kapitaalverzekeringen. Kortom, de 'Annuity puzzle', voor zover die al bestaat, vind zijn oorsprong voornamelijk in de lagere sociaaleconomische klassen van de Nederlandse bevolking.

Ons econometrische model staat ons echter toe een andere oorzaak aan te dragen: meetfouten. In elk databestand zitten meetfouten; in vragenlijsten, via de computer ingevuld door leden van het huishouden, zullen deze relatief vaak voorkomen. De meetfout die wij onderzoeken beslaat het bezit van de diverse producten. Naast de mogelijkheid dat een persoon de waarheid invult (hij/zij heeft wel een polis, en vult in dat hij/zij deze inderdaad bezit; idem voor niet-bezitters) zijn er twee mogelijke meetfouten: een persoon heeft een polis, maar stelt in het antwoord geen polis te bezitten, en omgekeerd. Waarom de persoon een antwoord geeft dat afwijkt van de waarheid is niet duidelijk, en zullen we in nader onderzoek proberen toe te lichten. Mogelijke spelen veranderingen in de samenstelling van het huishouden (zoals echtscheiding), vergeetachtigheid of verveling tijdens het invullen van de vragenlijst een rol. In elk geval vinden wij een grote rol voor meetfouten: wij schatten dat 32% van de bezitters invult geen lijfrenteverzekering of koopsompolis te bezitten. Voor 12% geldt het omgekeerde: zij geven aan wel een lijfrenteverzekering of koopsompolis te bezitten, terwijl wij inschatten dat ze in de groep niet-bezitters horen. Deze forse afwijkingen zijn onderhevig aan statistische onzekerheid, maar letterlijk genomen zou het percentage bezitters hiermee stijgen van 32% naar 56%. Meetfouten kunnen dus een belangrijke oorzaak van de 'Annuity puzzle' zijn.

In hoofdstuk 5, geschreven met Rob Alessie en Viola Angelini, keer ik terug naar de vraag wat de effecten zijn van pensioenen op spaargedrag. Wij nemen een Europees perspectief, en maken gebruik van recent verzamelde gegevens over huishoudens in 13 Europese landen. Deze data zijn uniek, in dat ze, naast de typische vragen over inkomen, vermogen en samenstelling van het huishouden, vragen stellen over wat zich in het verleden heeft afgespeeld. De respondenten zijn 50 jaar of ouder, waardoor we doorgaans niets weten over gebeurtenissen in het verleden die een belangrijke rol kunnen spelen in hedendaags vermogen of gedrag. Iemand die 10 jaar lang werkloos is geweest zal een andere pensioenopbouw kennen dan iemand die altijd fulltime heeft gewerkt. Met deze pan-Europese vragenlijst kunnen we deze informatie wel achterhalen, en kunnen we inschatten hoeveel het huishouden in het verleden in totaal aan arbeidsinkomen heeft verdiend. We tonen aan dat deze informatie uitermate nuttig is in het schatten hoeveel meer of minder huishoudens sparen door veranderingen in hun pensioeninkomen. Onze resultaten suggereren dat een gemiddeld Europees huishouden 47-61 eurocent meer spaart als het pensioenvermogen met 1 euro afneemt. Dit stijgt tot 78-87% als we alleen kijken naar liquide besparingen. Deze percentages suggereren dat een hervorming van het pensioensysteem, met lagere pensioenuitkeringen als gevolg, zal leiden tot een toename van private besparingen, en dus een toename van het vermogen van huishoudens. Hierdoor worden de negatieve gevolgen van de hervorming deels teniet gedaan, echter in onvoldoende mate om dezelfde levensstandaard te garanderen. Ook vinden we dat er belangrijke verschillen zijn qua opleiding: laagopgeleiden zullen hun gedrag nauwelijks aanpassen, en lopen dus grote risico's er flink op achteruit te gaan als het pensioensysteem op de schop gaat. Dit in tegenstelling tot hoogopgeleiden, die hun gedrag wel aanpassen aan de veranderde omstandigheden. Tot slot vinden we dat pensioenhervormingen in Griekenland, Italië en Spanje de meest desastreuze effecten zullen hebben, als gevolg van het uitblijven van genoemde spaarreactie.

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