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Essays on Consumption Choice, Well-Being, and Pension Design

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Chapter 1

Introduction

People across different cultures and socio-economic groups agree that well-being is their most important goal in life (Diener (2000)). Improving human well-being is also the most important goal of economic research. As Ben Bernanke puts it: "The ultimate purpose of economics, of course, is to understand and promote the enhancement of well-being".[1] This thesis investigates consumption choice, its impact on human well-being, and how pension design should look like under non-standard consumption preferences.

The last centuries can be coined as the age of consumer society. Nowadays, people can choose between more commodities and services than ever before. Consumption and consumer behavior are also one of the leading topics in the social sciences. Especially in economics, consumption is very important. Households' final consumption expenditure — the so-called private consumption in economic accounting equations — constitutes the highest share of countries' gross domestic product. For example, the consumption-GDP ratio amounts to 69 percent in the United States and 58 percent in Germany (World Bank (2014)). In macroeconomics, consumption determines aggregate demand, generates jobs, and quite generally keeps the economy going. Moreover, it causes economic cycles and serves as an important vehicle for stimulus packages (multiplier effect). In microeconomics, consumption is important for individuals and households. They care about what they can afford to buy; how they split their income between consumption, savings, and debt reduction; and what they should consume in order to improve their well-being.

It is questionable, whether the extensive focus on consumption — a source of external gratification — improves human well-being, or even prevents people from pursuing more important goals. In fact, the association between consumption choice and humans' quality of life is multifaceted and complex. Consequently, it is far from being fully understood.

[1] Speech by Ben S. Bernanke at the 32nd General Conference of the International Association for Research in Income and Wealth, Cambridge, Massachusetts, 6th August 2012. At this time he was Chairman of the US Federal Reserve.

This dissertation seeks to illuminate certain aspects of this relationship, without the pretension of exhaustiveness. In particular, the thesis tries to foster the understanding of how consumption composition and relative consumption affect human decisions, and how these decisions impact humans' living conditions or their evaluation thereof. In this introductory section, the terms well-being and humans' quality of life are used interchangeably, and have a very general meaning. I elaborate on the context-specific meaning in the respective chapters of this thesis.

To promote well-being, economists need to understand what people want, what drives their decisions, and what has the highest potential to deliver well-being. Empirical research raises important questions by analyzing the data and discovering empirical regularities. Subsequently, theoretical research can build theoretical models that explain these regularities and the underlying human behavior. Ultimately, empirical research has to test and validate the existing theoretical models. Thus, economic research is most illuminating and fruitful, if there is a back-and-forth between theory and empirics.

In line with this reasoning, the chapters of this thesis use theoretical and empirical methods. The second chapter is empirical and purely data-driven. It looks at the impact of specific consumption goods on subjective well-being (SWB) — using individual data. The third chapter is also empirical, but model-driven. It estimates the coefficients of a generalized expected utility model with additive habits. In particular, it investigates the strength of internal habit formation and social comparison (relative consumption) — using household consumption data. The fourth chapter is theoretical. It employs a behavioral life-cycle model, in which individuals have non-standard consumption preferences and risk attitudes. The model is used to analyze the preferability of different pension schemes in Germany.

Overall, there is a strong connection between all three chapters. They are all concerned with consumption choice. Moreover, they look at the effect of consumption on humans' quality of life — irrespective of whether it is represented by utility, a value function, or reported subjective well-being. Furthermore, they lay emphasis on micro-economic questions, although macro-economic implications are sketched as well. Finally, all chapters consider psychological underpinnings, as well as insights from happiness and behavioral economics, which are typically ignored by mainstream economics. Mainstream economics, for instance, stresses the maximization of measures such as wealth, income, growth, revenue, or profit. In contrast, happiness economics views well-being as the ultimate goal to be maximized.[2] Behavioral economics seeks to improve economic analysis through more reasonable assumptions on human behavior and humans' cognitive capabilities.

[2]Although neoclassical economics and welfare economics see the increase of human well-being as an important goal, they are not subsumed under the term happiness economics.

That said, this dissertation's primary goal is to analyze the effect of consumption choice on humans' quality of life through the lens of behavioral and happiness economics.[3] This means, I maintain the economic perspective on all investigated questions, while considering inter-disciplinary insights — primarily from psychology, sociology, and neuroscience. This procedure is supposed to shed fresh light on old questions, or to raise new questions.

There is no arguing with the intuitive understanding that more consumption is better, but the question is, whether it is necessarily much better. People devote considerable efforts towards income accumulation in order to stimulate consumption opportunities. This is sometimes referred to as the work-spend treadmill. Apparently, more income provides more consumption opportunities. But how exactly does a person's well-being depend on consumption? This thesis's chapters touch upon three different aspects of how consumption choice influences human well-being.

First, the impact of consumption composition on subjective well-being is analyzed.[4] In economic models, consumption is — for simplicity — often treated as one composite measure, without disentangling it into several consumption goods or categories. But is it possible that an *equal amount of money* spent on two different goods could have a different impact on well-being? In other words, is it possible that people improve their well-being by choosing the goods that deliver the biggest happiness bang for the buck? The question is motivated by psychology research (Scitovsky (1976), Frank (1985), Van Boven and Gilovich (2003), Van Boven (2005), Howell and Hill (2009), Nicolao et al. (2009)), but the economic literature provides no answer, so far. Chapter two seeks to fill this gap.

Second, the impact of relative, or reference-dependent, consumption on economic utility is explored. Already Smith (1759), Veblen (1899), and Duesenberry (1949) suggested that it might not just be absolute consumption that matters, but also relative consumption. People compare themselves constantly; either with their own past situation (inward-looking), or with other people (outward-looking). In the economic literature this is typically addressed by models of internal and external habit formation (Abel (1990), Constantinides (1990), Campbell and Cochrane (1999), Korniotis (2010), Grishchenko

[3] Actually, when considering the history of economics, it should not be necessary to stress the term *behavioral*. For a long time, economics — being a social science — approached human behavior in a very realistic fashion. Within the last century, though, the common practice was to model decision-making, as if it was conducted by rational super-computers. The main reason is that this allows a simplification of complex problems and a convenient mathematical representation. This line of research is often coined as mainstream or orthodox economics. Nowadays, more realistic decision-making enjoys a revival — as can be seen from the surge of behavioral papers in prestigious journals within the last years.

[4] Those who are skeptical about measures of SWB are referred to a large literature that demonstrates the ability of SWB to approximate actual well-being very well. See chapter 2 for a discussion and references.

(2010)). Micro-econometric evidence on the strength of the respective forces (internal and external) is still inconclusive, and only based on food consumption data. Chapter three provides more general evidence based on total household consumption data.

Third, the impact of boundedly rational consumption preferences on life-cycle and retirement well-being is investigated. As mentioned before, mainstream economic models usually impose the assumption of perfect rationality. But if decision-problems become extremely complex, people are far from being perfectly rational. Rather, they are boundedly rational and apply simplifying rules to solve difficult decision problems (Ford et al. (1989), Payne et al. (1993), Gabaix and Laibson (2005)). Hence, chapter four adds the feature of bounded rationality to reference-dependent consumption preferences. The subsequent paragraphs provide a short overview of this thesis's chapters.

The second chapter investigates how different consumption goods are associated with SWB. In contrast to the objective concept of economic utility, SWB refers to humans' self-evaluated well-being. SWB is an umbrella term that captures cognitive and affective well-being. *Cognitive* well-being is the evaluation of life in general. It is determined through critical thinking and commonly measured by a life satisfaction scale. *Affective* well-being captures feelings and emotions. Happiness and depression scales are two common measures for positive and negative affective well-being, respectively. In this chapter, three different components of SWB are used (life satisfaction, happiness, and depression), because they are suspected to be differently associated with total consumption, specific consumption goods, and other covariates. It is interesting that there are many studies on the association of income and SWB (Easterlin (1974), Stevenson and Wolfers (2008), Diener et al. (1985), Powdthavee (2010)), but nothing on how to spend income in order to enhance SWB. This is the literature gap that chapter 2 seeks to fill. I find that it pays off to disentangle the three components of SWB, since they are indeed differently associated with consumption goods. Total consumption is positively associated with SWB. In particular, more consumption seems to increase positive states of well-being (life satisfaction and happiness), but it does not seem to alleviate negative states of well-being (depression). When total consumption is decomposed into consumption categories, only some categories are responsible for the consumption-SWB relationship. Especially, conspicuous and experiential goods contribute to higher SWB. Nonetheless, some materialistic consumption goods, such as personal care and clothing, have a sizable positive effect on SWB as well. To derive valid causal inference, I account for the potential endogeneity of consumption in the SWB equation. The main reason to suspect endogeneity is simultaneous determination. Put differently, consumption might not only influence SWB, but people who enjoy higher well-being might also display different consumption patterns. Instrumental variable estimation suggests a causal effect

of consumption on SWB.

The third chapter elicits the weights of relative consumption in a generalized expected utility model, using monthly household consumption data. In particular, it investigates the strength of internal and external habit formation in consumption. Internal habit formation corresponds to adaptation to past own consumption. External habit formation corresponds to the social comparison with others' consumption. In economics, the habit hypothesis is primarily used to explain empirical regularities in macroeconomics and finance. But, the strength of relative consumption preferences is also interesting for normative research that evaluates individual well-being and social welfare. Hence, the estimated weights could provide guidance to theorists and public policy makers. Empirical studies based on aggregate data (macro-evidence) leave the micro-behavior unexplored and ignore the role of individual heterogeneity. The micro-econometric evidence on habit formation is still inconclusive. Moreover, it is almost exclusively based on food consumption data, which constitutes a bad proxy for total consumption. Shea (1994), for instance, shows that food consumption preferences differ considerably from consumption preferences of other goods. Additionally, Attanasio and Weber (1995) strongly reject the idea that food consumption and other consumption preferences are separable. Essentially, the derived coefficients from food consumption data cannot be generalized to total consumption. (Dynan, 2000, p. 401) states that "the key question — whether the strength of habits in food is the same as that for the average consumption good — has no obvious answer". Answering this key question is the main contribution of the third chapter. A new data set is used, which provides total household consumption data and does rely on questionable proxies thereof. There is significant evidence for internal and external habits in consumption preferences. The external habit effect is much stronger than the internal effect. The results are robust to several sensitivity checks.

The fourth chapter deals with the question how non-standard consumption preferences might impact optimal pension design. The decision-preferences are related to those in the previous chapter, but the current analysis dispenses with perfect rationality and models preferences as lexicographic. In particular, the internal and external references are not considered simultaneously, but one after the other: People care only about themselves and ensuring a minimum of consumption for the future, before they start to care about external consumption references (social comparison) and maximization of resources. This feature corresponds better to bounded rationality and simplified decision rules. The question of optimal pension design is an important agenda of economic research. Due to increasing longevity and declining birth rates, the question is also a priority on the political agenda. The demographic change, which is unlikely to be completely absorbed by productivity growth, renders the currently-in-place Pay-As-You-Go systems (non-funded)

unattractive. In particular, it puts a higher pressure on the working-age generation of the economy or leads to non-sustainability of public pension accounts. According to Deutsche Rentenversicherung Bund (2010), the expenditures for old-age pensions amount to 245.83 billion Euro in Germany, but only 181.33 billion Euro were collected through regular contributions. The remaining 64.5 billion Euro, accounting for 26 percent, had to be paid by the German government — but not from the budget that is designated for old-age pensions. A person's retirement resources depend on the public pension benefits and individual savings that were accumulated over working life. There is a sizable return-gap between non-risky and risky assets. Hence, the individual savings crucially depend on allocation of assets. Unfortunately, mainstream economic models are not very successful in predicting people's life-cycle asset allocation patterns. The proposed model, which builds on the non-standard decision-preferences, makes a better prediction. I investigate whether a transition towards a funded pension scheme is desirable, and whether different income classes could benefit from different pension schemes. The rationale is that a non-funded pension component provides better downward risk protection for the low-income earners, whereas a funded pension component is more appealing to rent-seeking, high-income earners. The results show that a funded pension scheme is more promising than a PAYG pension scheme, for all income classes. The simulation considers reasonable demographic and financial market projections for Germany's future within the next decades. The analysis is set up in a partial equilibrium model without a general equilibrium feedback mechanism.

Each of the subsequent chapters constitutes a self-contained research paper. The specific contributions, limitations, and implications are discussed in detail within each chapter. To all of them applies one common limitation: consumption is not the only factor that contributes to human's quality of life. There are many other factors. I recognize that some of these factors are of equal, or even higher, importance for humans' quality of life. Nevertheless, the focus on consumption is chosen for two reasons. First, this allows me to investigate consumption choice in greater detail and with nuanced sub-questions. Second, certain other factors — especially biological and chemical ones, such as, genetics, nutrition, and hormones — are better analyzed by scientists of the specific fields, who know the subject much better.

Chapter 2

The Pursuit of Subjective Well-Being through Specific Consumption Choice

2.1 Introduction

This paper investigates the relationship between consumption and subjective well-being (SWB). Specifically, it tests whether different consumption categories are associated differently with SWB. More figuratively, if you had 100 Euros to enhance your well-being, would you spend it on a meal with friends, a sports ticket, or new shoes? At first, the empirical regularities are examined. Secondly, I analyze whether consumption has a causal effect on SWB.

For several decades, SWB was primarily studied by psychologists, but the question, how consumption behavior impacts humans' well-being is also extremely interesting for economists.[1] This has four major reasons. First, people across different cultures and socio-economic groups agree that SWB is the highest goal in life (Diener (2000)). Second, people widely hold the belief that money improves their well-being, and consequently, devote considerable efforts to accumulate more income. Third, SWB might provide a valuable empirical measure that approximates economic utility (Frey and Stutzer (2002)).[2] Since utility is immeasurable, SWB data can provide econometricians with new opportunities to test economic assumptions and theories.[3] Fourth, there is a gap in the

[1] Further discussions how economics can benefit from studying SWB can be found in Frey and Stutzer (2002), Bruni and Porta (2007), Clark et al. (2006), and Layard (2011).

[2] Broadly speaking, utility of consumption is a mathematical construct, which represents the satisfaction that a customer experiences through the acquisition of consumption goods.

[3] Undoubtedly, some economists are, and will remain, skeptical about the approximation of utility through subjective well-being data. Nonetheless, they can hardly argue that it is not at least a complementary view that deserves investigation. According to Frey and Stutzer (2002), SWB is a broader construct than economic decision utility, because it subsumes experience utility (derived from an outcome), as well as procedural utility (derived through the process and conditions that lead to an outcome).

economics literature. Although there are many studies on income and well-being (Easterlin (1974), Stevenson and Wolfers (2008), Diener et al. (1985), Powdthavee (2010)), the literature is surprisingly silent about how individuals spend their income and how this spending choice affects SWB. In other words, the impact of consumption composition on SWB is unexplored. Ultimately, this is a question of spending efficiency with implications for consumers and scholars. Consumers want to know which consumption goods deliver the largest impact on well-being. Given income, they face a trade-off problem on how to spend most efficiently with respect to SWB-enhancement. Scholars seek to understand what drives people's consumption choice, whether it is in line with economic utility maximization (efficient), and if not, which "hidden constraints" keep people from choosing efficiently.[4]

There are two potential reasons why there has been little effort to understand the impact of consumption composition on SWB, so far. One reason might be that economic utility theory is so convincing that empiricists saw no need to test it. *A utility-maximizing agent is supposed to distribute his income most efficiently, so that no higher utility is possible by spending income differently*. Another, and more likely reason, is that appropriate micro-econometric data was not available until now.

Before I describe the contributions of this paper, it is imperative to discuss well-being terminology. First, the word "subjective" in SWB emphasizes that perceived, rather than objective well-being is analyzed. Second, terms such as happiness, life satisfaction, and quality of life are often used interchangeably, which is misleading. Research shows that these terms refer to different elements of well-being, which can strongly diverge for the same person (Diener (1994)). Third, researchers agree that SWB is an appropriate umbrella term (or hybrid concept) that captures both *cognitive* and *affective (emotional)* elements of well-being (Diener (2000), Frey and Stutzer (2002)). Cognitive well-being means that people evaluate their life through critical thinking. Whenever people think about their financial situation, work environment, health status, or social ties, this refers to cognitive well-being. Affective well-being, however, refers to emotions, feelings, and experiences. Whenever people read a pleasant book, enjoy ice cream, or feel frustrated because of the cloudy sky, this captures affective well-being. As the above illustrations indicate, affective well-being can be positive and negative.

This paper fills an important gap in the literature by investigating the effect of consumption composition on SWB. A similar study is conducted by DeLeire and Kalil (2010), albeit with a severely limited data set, as they point out themselves. To improve upon their findings, I use a new representative sample of US individuals (RAND

[4]The term hidden constraints refers to any explanation of non-efficient consumption choice, which includes information constraints, budget constraints, social pressure, reinforcement, self-control constraints, bounded rationality, and behavioral constraints in general.

American Life Panel (2013)). The contributions of this paper are both substantive and methodological. First of all, I use three different measures for SWB. Remember that SWB consists of three elements: cognition, positive affect, and negative affect. Life satisfaction captures the cognitive element of SWB. Happiness captures positive affect and depression captures negative affect. Disentangling these three components allows to study in detail through which channels — emotion or thinking — spending behavior impacts well-being. In contrast, DeLeire and Kalil (2010) use only life satisfaction. Second, the use of panel data allows me to account for individual heterogeneity (fixed effects), and endogeneity of consumption that is due to joint determination.[5] Only in this way the coefficients allow for a causal interpretation. Addressing fixed effects is especially important in SWB research, since a large share of a person's well-being variation is due to personality traits (Weiss et al. (2008)). Personality is also likely to affect the relationship between consumption and well-being. A materialistic person, for instance, might be influenced by different consumption goods than a non-materialist (Kasser (2002)).[6] Third, the data set contains more than 77,000 observations on the different consumption categories. A-priori, this allows a much more reliable estimation compared to a few hundred observations. DeLeire and Kalil (2010) have only 860 complete observations, before they increase their sample to 1,733 observations through imputation techniques (artificially created data points). Moreover, their data is non-representative, because it covers only relatively old people of the health and retirement study (HRS). Fourth, I use ordered probit regressions to address the ordered, categorical nature of SWB data. In this particular case, the three dependent variables (life satisfaction, happiness, and depression) are measured on a one to five scale. If the dependent variable is categorical, the ordered probit regression has several advantages over linear estimation methods: a) avoiding out-of-bound predictions, b) allowing more efficient hypotheses tests, and c) capturing non-linearity in the explanatory variables. In addition to the four contributions, I form ex-ante predictions based on previous studies, and refrain from ad-hoc explanations of my results. To sum it up — to my best knowledge — this is the first study that tackles the aforementioned research question with a large, representative panel data set and appropriate econometric methods.

There are four main results. First, consumption is significantly associated with SWB. Second, only 7 out of 14 consumption categories are responsible for this association.

[5] DeLeire and Kalil (2010) use cross-sectional data, but include five personality traits to address individual heterogeneity. Still, people display individual heterogeneity that goes beyond just five personality traits. More importantly, the potential endogeneity of consumption due to simultaneous determination cannot be addressed in this way. Also note that personality traits are basically time-invariant and drop if fixed-effect or first-difference transformations are applied.

[6] Ger and Belk (1993) view materialism as a collection of personality traits (envy, non-generosity, possessiveness, and preservation). Contrary, Richins (1994a) and Richins (1994b) see materialism as a value (or belief) on the importance of possessions.

Personal care & clothing, dining out, leisure activities, sport, and spending on children's education is positively related to SWB. Health care and care for children and elderly is negatively related to SWB. Third, consumption impacts SWB mainly through experiential and conspicuous purchases, albeit materialistic consumption in form of personal care and clothing has the strongest effect on SWB. Fourth, endogeneity tests and instrumental variable estimation allow for a causal interpretation of the results. Moreover, the findings are robust to variations in controls, estimation technique, categorization of consumption types, and whether consumption categories enter in level or ratio form.

The results suggest that people could at least re-evaluate existing spending patterns and potentially re-adjust consumption composition in order to achieve higher SWB. Nevertheless, normative statements are only speculative, as long as no theory exists that explains why people behave the way they do. The latter is a challenging agenda for future economic work. Specifically, theory should help to understand why people choose particular consumption goods, even though other consumption choices are associated with higher levels of SWB.

The remainder is organized as follows. Section 2 presents a literature survey and forms hypotheses for the empirical part. Section 3 describes the data set. Section 4 discusses the limitations of a linear econometric model and provides an extension to the ordered probit model. It also points out econometric issues and the interpretation of the ordered probit coefficients. Section 5 provides the main results and the sensitivity analysis. Finally, section 6 concludes.

2.2 Literature Review and Hypotheses

2.2.1 Measuring Subjective Well-Being: Validity and Reliability

To find out what affects SWB, it is necessary to measure it first. Note the fundamental difference between happiness research and mainstream economic research. The well-being literature builds on humans' subjective evaluation of their actual well-being — a stated preference approach. Contrary, economic theory derives conclusions about people's preferences by observing their behavior — a revealed preference approach.[7] For the remainder of this paper, it is essential to trust people's self-assessment. After all, they are the best judges of their own well-being. There is also a broad literature that demonstrates that self-reported, or subjective well-being, is not just random noise, but rather a reliable and valid approximation of actual well-being (Blanchflower and Oswald (2004), Konow

[7] For most questions both approaches yield identical results, but sometimes there can be major differences. There is, for instance, a strong gap between people's intended retirement savings behavior and their actual preparation for retirement.

and Earley (2008), Larsen et al. (1985), Fordyce (1986), Argyle (1989), Watson and Clark (1991), Myers (1993), and Pavot and Diener (1993)). In particular, SWB is highly correlated with the following aspects:

1. Objective characteristics
2. A person's recall of positive and negative life-events
3. Ratings of the person's happiness by friends and relatives
4. Ratings of the person's happiness by his or her partner
5. Duration of authentic smiles during social interaction[8]
6. Stress-resistance (heart rate, blood-pressure, skin-resistance)
7. Psychosomatic illnesses (digestive disorders and headaches)
8. Electroencephalogram measures of pre-frontal cortex brain activity

Additionally, the different components of SWB fulfill the criteria of discriminant validity. Although they are correlated, they measure different aspects of well-being (Lucas et al. (1996)). The same person can, for instance, be very satisfied with life (cognition), but still feel rather unhappy most of the time (affect).

2.2.2 Theories on Well-Being

There are three main theories on well-being. The first theory explains well-being through the satisfaction of needs or goals. Freud's "pleasure principle" (Freud (1976)) and Maslow's "hierarchic need pyramid" (Maslow (1943)) are two prominent examples thereof. The second theory claims that well-being is derived from activities or processes. An important example is the "flow theory" by Csikszentmihalyi (1975), in which "flow" means that people engage in interesting activities that match their skills. In contrast to the first theory, it is not the goal itself that promotes well-being, but the underlying process directed towards the goal achievement. Both theories agree that the environment has an influence on well-being. In contrast, the third theory views well-being as predetermined and highly stable.[9] It is true that genetic inheritance — which is predetermined — is the most consistent predictor of individual well-being. According to Lykken and Tellegen

[8] An authentic (Duchenne) smile occurs when both the zygomaticus major muscle and the obicularis oris facial muscles are activated. People can tell the difference between an authentic and a faked smile.

[9] Recent studies challenge this theory. Neuroscience shows that mono-zygotic twins, with identical genes, can still display different DNA activation. Moreover, Easterlin (2006) demonstrates that different domains of satisfaction vary considerably over the life-cycle, but the aggregation into an overall life satisfaction measure makes life satisfaction appear flat or stable.

(1996), more than 50 percent of SWB's variation is due to "the great genetic lottery that occurs at conception" (Weiss et al. (2008)).

Important determinants of SWB include: physical health, mental health, personality, weather, religion, political freedom, justice, gender, ethnicity, age, marriage, education, nutrition (Blanchflower et al. (2013)), employment status, culture, social contact, relative concerns, and money.

Most theoretical explanations for the relationship between consumption and SWB fit into the first theory of well-being: consumption as vehicle for need satisfaction. According to Maslow (1943) human needs can be classified into five categories, subsequently ordered by hierarchy: basic, safety, social, status, and self-actualization needs. People with little money can only afford to satisfy their basic and security needs. With increasing income, more consumption opportunities arise and people can satisfy higher needs. After basic and security needs are met, people want to satisfy their social needs and aim for closer social ties. This can be achieved through consumption purchases that facilitate social connections. Once they reach a certain income, they can also afford to signal their status by spending on conspicuous goods (status, visible, or luxury goods; Veblen (1899), Charles et al. (2009)). Finally, humans strive for self-actualization, for instance, through art, music, and travel.

2.2.3 Previous Literature

Traditionally, economic research operated on Pigou's dictum "that there is a clear presumption that changes in economic welfare indicate changes in social welfare in the same direction [...]" (Pigou (1924)). In fact, there is a vast economic literature on money and SWB, typically asking whether income is associated with (correlation), or brings about (causality) well-being. The results are still inconclusive. Easterlin is the first economist who investigated this question empirically (Easterlin (1974), Easterlin (1995)), providing three main results. First, in the same country rich people enjoy higher SWB than poor people. Second, SWB remains constant over time, although income rises considerably. Third, there is little difference in SWB between rich and poor countries. The first result suggests a positive money-SWB relationship, whereas the two latter results question it. Since the three results seem incompatible (without further explanation), they are coined *Easterlin-Paradox*. Some authors confirm Easterlin's results (Diener et al. (1985), Frey and Stutzer (2002), and references therein) while others reject them (Stevenson and Wolfers (2008), Sacks et al. (2013)). Sacks et al. (2013) stress the importance of income for SWB, and propose five stylized facts: a) richer people are happier than poorer people, b) richer countries are happier than poor countries, c) well-being and income rise jointly over time, d) there is no satiation point, and e) the

magnitude of facts a to c is approximately equal. Powdthavee (2010) provides causal evidence for an effect of income on SWB. Although no final consensus is reached yet, at least the within-country studies agree that income has a significant, albeit moderate, effect on SWB.

The main explanations for the diverging, and at times paradoxical results, are adaptation (hedonic treadmill), aspiration (increasing expectations), and social comparison (Smith (1759), Veblen (1899), Duesenberry (1949)).[10] Especially social comparison in conspicuous goods might explain why SWB does not change over time — at least not in affluent societies, where basic needs are met and status is a zero-sum game. Note that today's borderline poor live as well as the upper class from several decades ago, but they still feel poor. Mayraz et al. (2009) show that men are stronger influenced by relative concerns than women.[11] Boyce et al. (2010) suggests that social ranking is more important than the size of relative differences. Other explanations for the weak income-SWB relationship include diminishing returns and adverse effects on other determinants of SWB (e.g., increased suicide, higher CO2 emissions, loss of social ties; Diener and Diener (1995), Putnam (2000), Pugno (2008)).[12] Furthermore, the ambiguity of results is attributed to cultural differences, methodological failures, inconsistent data (across time and countries), and the failure to address price-changes of goods and needs.[13]

Despite the numerous studies on income and SWB, it is surprising that economic research is silent about how individuals spend their income and the effects of this on SWB. Put differently, the aforementioned studies do not investigate how, or through which channels, income delivers (or is associated with) well-being. Income data alone provides insufficient information (Meyer and Sullivan (2003)), because it remains unclear whether income is used for saving, consumption, or to pay down debt. Before well-being research confirms or rejects the "folk wisdom" that money buys happiness, it is important to scrutinize the methodology, measures, and results of existing studies. More elaborate approaches that target consumption choice are scarce and to my knowledge non-existent in the economics literature.

The psychology literature quite generally advises people to spend their income on experiential goods rather than materialistic ones (Scitovsky (1976), Frank (1985)). Note that economic theory on utility-maximizing agents needs no such normative recommenda-

[10] Dutt (2009) explains the six main channels through which relative consumption influences individual consumption decisions.

[11] Moreover, the perceived role and the actual role of relative income differ considerably. People underestimate the degree to which they compare themselves.

[12] Howell et al. (2013) show that income affects SWB beyond basic needs.

[13] Note that needs can remain constant, but it becomes more expensive to satisfy the same need. For example, a person's security need might no longer be satisfied by food and shelter, but require a home security system, a bullet-proof car, or a gun.

tion. If an individual can afford it, has perfect information, and is perfectly rational, it will always choose the allocation of resources that is optimal. The experience recommendation of psychology research is motivated by four major aspects. First, people adapt more slowly to experiences than possessions, which means the benefits accrue for a longer time. Second, experiences are more open to positive re-interpretation in the future. Even if the vacations had unpleasant moments, subsequent re-evaluation is biased and considers more of the good moments. Third, experiences have greater social value than possessions. It is simply more fun to talk about things that you do, or did, than about things that you own. Fourth, experiences are less prone to social comparison. Every experience is unique, whereas it is fairly easy to compare the characteristics of materialistic goods.

The first empirical tests on this issue, indeed, suggest that humans derive more well-being from experiential goods (Van Boven and Gilovich (2003), Van Boven (2005), Howell and Hill (2009)). However, there is more to the story. Nicolao et al. (2009) confirm the superior role of experiential goods for SWB, but only as long as consumption purchases turn out positively. In contrast, if experiential purchases turn out negative (e.g., bad vacation or boring event) they tend to have a stronger negative impact on SWB than material goods. In other words, experiential spending effects have a higher variance. Thus, the favoritism of experiential consumption depends on the probability of a positive post-purchase evaluation. Nicolao et al. (2009) attribute this to a slower mental adaptation process to experiences, compared to possessions. Hence, both positive and negative experiential effects last longer than materialistic effects.

Last but not least, the relationship between consumption and SWB, as well as income and SWB, is not necessarily a one-way direction. It is also possible that well-being affects consumption, or income. De Neve and Oswald (2012) find a dynamic relationship, in which happiness improves the financial situation several years later. Guven (2012) shows that people with higher life satisfaction consume less and save more. He suggests that this is due to higher self-control and a greater tendency to plan for the future. Well-being studies should test, and if applicable, account for simultaneity, otherwise coefficients might be severely biased.

2.2.4 Assigning Consumption Categories to Consumption Types

Before hypotheses are formed, it is first necessary to define consumption types, and then, to assign consumption categories to these consumption types. I recognize that any classification of consumption categories is subjective to some degree. Nevertheless, it is imperative to draw a distinction line in order to test the hypotheses of the next section.

There are two dimensions of consumption types. The first dimension differentiates between materialistic and experiential consumption; both being mutually exclusive. This

means that a consumption good labeled as experiential cannot be materialistic, and vice versa. The second dimension differentiates between basic and conspicuous consumption. Again both types are mutually exclusive. Across the two dimensions of consumption types, an overlap is possible. A conspicuous consumption good, for instance, can be materialistic (shoes) or experiential (vacation).

The American Heritage Dictionary defines *conspicuous consumption* as follows: "The acquisition and display of expensive items to attract attention to one's wealth or to suggest that one is wealthy." This definition captures the spirit intended by Veblen (1899), who coined the term conspicuous consumption. Conspicuous consumption is also referred to as visible or status consumption. *Basic consumption,* on the other hand, refers to goods that are only consumed for their utilitarian value; not to signal status. Broadly speaking, basic consumption satisfies the basic and security needs of Maslow's need pyramid, whereas conspicuous consumption satisfies higher-order needs.

To assign consumption categories, I rely on the visibility index by Heffetz (2011).[14] The index understands visibility, or conspicuousness, in terms of how noticeable a consumption good is by other people. An index value of 1 corresponds to a very conspicuous good and a value of 0 indicates no conspicuousness (visibility). I assign all consumption goods with an index value above 0.5 to the conspicuous type. All other consumption goods (0.5 and below) are assigned to the basic type, leading to the following classification:

- Basic consumption: health care, care for children & elderly, utilities & housing, mortgage, household products, household services, gasoline
- Conspicuous Consumption: food & beverage (home), dining out, leisure & entertainment, sport, child education, personal care & clothing, car-related[15]

Many studies suggest that experiential goods stimulate SWB more than materialistic ones. But, there are no studies that give a straight answer on how to assign consumption goods into materialistic and experiential. Also, there is no index that facilitates a classification. In the absence of such assignments, theories can be tested only approximately. Moreover, research results depend heavily on the framing of the questionnaire. If someone, for instance, affirms that he prefers experiences over possessions this is very vague and does not necessarily mean that he would prefer a movie night (experience) over new shoes

[14] See table 4 of his paper, particularly, the first three columns.

[15] There is a difference between car and car-related consumption. Car consumption refers to the purchase of the car itself, whereas car-related consumption refers to interest and principal. Heffetz (2011) rates the car purchase as very conspicuous, but does not include principal and interest in his consumption categories. Many people, however, do not buy a car but use leasing contracts, which leads to interest and principal payments. I assume that interest and principal proxy for car consumption, for which I have no data. Consequently, I attribute car-related consumption (interest and principal) to conspicuous consumption.

(possession), assuming both purchases have the same price. Moreover, the framing of such questions (experience over possession) lends itself to an affirmation, since being considered materialistic is not desirable in Western societies and has a smack of egoism. Unfortunately, psychological research conveys the impression that the question of experiential versus materialistic consumption has been analyzed exhaustively with consumption data. In fact, existing studies either employ case studies with narrow consumption goods or provide theoretical (hypothetical) explanations why experience beats possession. Case studies, however, have only little general validity and theoretical explanations provide little guidance without being tested empirically.

To distinguish between materialistic and experiential consumption, I use the intention-based definition of (Van Boven and Gilovich, 2003, p. 1194). "*Material* purchases are those made with the primary intention of acquiring a material good: a tangible object [...]", for instance, a car, a flat-screen TV, or shoes. "*Experiential* purchases are those made with the primary intention of acquiring a life experience: an event or a series of events that one lives through", for instance, a restaurant visit, a vacation, or a balloon flight.[16] This results in the following assignment:

- Materialistic Consumption: food & beverage (home), utilities & housing, mortgage, health care, care for children and elderly, child education household products, household services, gasoline, car-related, personal care & clothing
- Experiential Consumption: dining out, leisure & entertainment, sport

Later on, I provide a robustness check for variations in these assignments (see results and appendix).

2.2.5 Hypotheses

The hypotheses are formed based on results from previous studies, which were already mentioned in section 2.2.3. To avoid redundancy, references and explanations are limited.

Hypothesis 1: Total consumption is positively associated with SWB (after other explanatory variables are controlled for). In the remainder, *positive* means increasing life satisfaction and happiness, but decreasing depression.

The hypothesis is a sensible prediction that is based on the results of the income-SWB relationship (Easterlin (1974), Powdthavee (2010), Stevenson and Wolfers (2008)).

[16] The definition of an experiential good differs from the definition of an experience good. An experience good refers to a product for which the quality is only known to the consumer after consuming it (Nelson (1970)). The opposite is called a search good.

At least at the individual level, higher income is associated with higher SWB. Hence, total individual consumption, should have a similar effect on SWB. After all, consumption is the realization of the choice opportunities that are granted by income.

Hypothesis 2: Consumption delivers only immediate gratification (short-term) and has no lasting value. Hence, it mainly impacts on the affective, short-term components of SWB (happiness, depression) and not on cognitive, long-term evaluations of SWB (life satisfaction).

Affective well-being, or feeling, is fugacious, and hence, only of short-term duration. In contrast, cognitive well-being is much broader and more persistent, since it evaluates the past, the presence, and also future prospects (Kahneman and Riis (2005)).

Hypothesis 3: Conspicuous consumption is associated with higher levels of SWB, compared to basic consumption.

The owners of conspicuous consumption goods enjoy higher well-being through the display of their superior economic wealth and status (Veblen (1899)). But, this leads to a zero-sum game for society as a whole, as not everyone can win the status competition (Curtis and Mukesh (2009)).

Hypothesis 4: Experiential consumption is associated with higher levels of SWB, compared to materialistic consumption.

Experiential goods are slower adapted to, more open to positive re-evaluation in the future (skewed perception over time), and have greater social value in communication compared to materialistic goods (Scitovsky (1976), Frank (1985)). Moreover, experiential goods increase relatedness and are less susceptible to (competitive) social comparison (Howell and Hill (2009))

Hypothesis 5: Based on hypotheses 3 to 4, those consumption categories that belong to both consumption types (conspicuous and experiential) should have the strongest, and most significant, association with SWB.

This implies that dining out, leisure & entertainment, and sport-related consumption

expenditures are expected to have a strong positive relationship with SWB.[17]

2.3 Data

The RAND American Life Panel (2013) comprises a large representative sample of people living in the United States. People are repeatedly asked to fill out the same survey on a monthly basis. Data is collected from May 2009 to April 2013. This provides panel data for 48 consecutive month. All observations are obtained after the financial crisis, and hence, major policy shifts (structural breaks) are unlikely. Moreover, the fact that all data points are collected within four years, guarantees that the wording and response categories of the questionnaire remain constant. Specifically, people are asked the same questions and are provided with the same set of answer possibilities. This eliminates the time-comparability problem that is found in other surveys.[18] Additionally, the high-frequency data — surveys are answered monthly — mitigates recall and reporting error.

2.3.1 Dependent Variable: SWB

There are three measures for SWB, which are life satisfaction (cognition), happiness (positive affect), and depression (negative affect).

The survey question for life satisfaction is: *"How satisfied are you with your life in general, all things considered"?* The response possibilities are: 1 = very dissatisfied, 2 = dissatisfied, 3 = neither satisfied nor dissatisfied, 4 = satisfied, and 5 = very satisfied.

The survey question for happiness is: *"How happy have you been in the last 30 days"?* The answer possibilities are: 1 = none or a little of the time, 2 = some of the time, 3 = a good bit of the time, 4 = most of the time, and 5 = all of the time.

The survey question for depression is: *"Overall in the last 30 days, how much of a problem did you have with feeling sad, low, or depressed"?* The answer possibilities are: 1 = none, 2 = some, 3 = moderate, 4 = severe, and 5 = extreme.

Happiness is more volatile than life satisfaction and depression, which is shown by the standard deviation in table 2.3. Transition matrices, which show how the three measures fluctuate from month to month, are given in table 2.1. The majority of people are satisfied (59 percent) with life, happy most of the time (54 percent), and only sometimes feel depressed (46 percent). Very dissatisfied people are extremely rare (1 percent).

[17] Note that the overlap of consumption types for these three consumption categories impedes the understanding of which channel drives (or dominates) the relationship.

[18] Surveys that cover many years, sometimes change the questions over time, re-frame the questions, or change the answer scales. For instance, people can answer a certain question on a 1 to 8 scale, but subsequently the same questions must be answered on a 1 to 12 scale. This impedes comparability.

Table 2.1: Transition Matrices (Numbers in Percent)

	current life satisfaction				
	1	2	3	4	5
life satisfaction last month					
1	50	36	8	5	1
2	6	55	24	14	1
3	1	12	57	29	1
4	0	2	9	81	8
5	0	0	1	36	63
total	1	9	17	59	14

	current happiness				
	1	2	3	4	5
happiness last month					
1	59	31	6	4	0
2	14	53	24	9	0
3	2	19	45	33	0
4	1	3	11	82	4
5	0	1	2	42	55
total	7	16	19	54	5

	current depression				
	1	2	3	4	5
depression last month					
1	79	20	1	0	0
2	16	72	11	1	0
3	4	40	47	8	1
4	2	14	38	39	7
5	1	8	15	37	39
total	38	46	12	3	1

The table shows the likelihood that current SWB takes on a particular value, conditional on the particular value of SWB in the previous month. Numbers are given in percent and are rounded to the nearest integer.

Life satisfaction: 1 = very dissatisfied, 2 = dissatisfied, 3 = neither satisfied nor dissatisfied, 4 = satisfied, and 5 = very satisfied. Happiness: 1 = none or a little of the time, 2 = some of the time, 3 = a good bit of the time, 4 = most of the time, and 5 = all of the time. Depression: 1 = none, 2 = some, 3 = moderate, 4 = severe, and 5 = extreme.

People who are happy none or little of the time are also rare (7 percent). Only 1 percent of people suffers from severe depression. The correlation coefficient of life satisfaction and happiness is 0.61, of life satisfaction and depression is -0.53, and of happiness and depression is -0.65. Note that happiness, which represents positive affect, and depression, which represents negative affect, are far from being perfectly negatively correlated. This finding is not limited to the present study. (George et al., 1995, p. 341) explain that different brain regions are responsible for positive and negative states of well-being: "[...] sadness and happiness affect different brain regions in divergent directions and are not merely opposite activity in identical brain regions".

Additionally, five domain satisfaction variables are available: total household income satisfaction, economic satisfaction, job satisfaction, social & family satisfaction, and health satisfaction. They are all coded on a 1 to 5 scale, with higher values indicating higher satisfaction.

2.3.2 Independent Variable: Consumption

The data set contains more than 20 consumption categories.[19] Summing them up gives a measure of total individual consumption. I assort the existing consumption sub-categories (narrowly defined consumption categories) into 14 consumption categories. The categories are similar to DeLeire and Kalil (2010), but not identical. They use only nine consumption categories. The difference is partly explained by the different data sources. Moreover, the greater sample size of this data set allows me to disentangle categories that are subsumed by DeLeire and Kalil (2010). For instance, they use the category *leisure* to subsume sport and leisure expenditures, whereas I differentiate between sport and leisure spending. Sport purchases are not necessarily conducted for the purpose of recreation and pleasure (like leisure), but can also aid long-term goals, such as fitness, beauty, and health. Another difference to DeLeire and Kalil (2010) is that I include consumption data for child education and money spent on care for children and elderly.[20] The consumption categories are summarized hereafter:

1. food & beverage (consumed at home)

2. health care (medications, health care services, medical supplies; not covered by

[19] The consumption categories exclude big ticket items (durables), such as, furniture, ovens, and dish washers. These big ticket items are bought very irregularly and infrequently, so that the purchase does not really coincide with the actual consumption. For goods that are bought at a regular monthly frequency, however, an approximate congruence between purchase and consumption is warranted.

[20] DeLeire and Kalil (2010) have only 860 responses with non-missing information, and hence, use mean imputation and multiple imputation techniques to increase sample size. My approach is more conservative. No imputation techniques are used and questionable values are eliminated in the data cleaning procedure.

insurance)

3. utilities & housing (rent, electricity, water, heating fuel, telephone, cable, internet)
4. mortgage
5. personal care & clothing (personal care and clothing, jewelry, watches, hair, shaving, skin, manicure, haircut)
6. car-related (interest, principal)
7. gasoline
8. household products (cleaning, laundry, yard, lawn, garden)
9. household services (dry cleaning, laundry, gardener hiring)
10. dining out (restaurant, cafe, bar, club)
11. sport (gym, equipment, bicycle, ski, boat)
12. leisure & entertainment (photography, stamps, reading, camping, movies, sport events, arts)
13. child education (tuition, books, board, supplies, room)
14. care for children & elderly

In brackets are the consumption goods (or sub-categories) that are then assigned to the consumption categories. The category *car-related* only includes the regular, monthly expenditures that are supposed to proxy the actual car consumption. Higher interest and principal hint at a more expensive car.

2.3.3 Control Variables

The control variables capture the financial situation, perceived health, and standard socio-economic aspects. In particular, I control for work income (before taxes and other deductions), credit card debt, stock ownership, home ownership, health coverage, family size, age, age-squared, age-cubic, employment status, self-employment, marriage status, education, state residency, retirement, health status, sleep issues, and being worn-out. Note that the variables health status, worn-out, and sleep issues are not objective (medical measurement), but reflect a person's subjective evaluation. In addition, there are time dummies (wave 1-48) and monthly dummies (monthly seasonal; 1-12), because the data is not price and seasonality-adjusted. In any case, severe price changes are not

expected within the short time span of data collection (four years), especially not on a month-to-month basis. The monthly dummies reflect differences in intra-year spending patterns, for instance, higher food expenditures in December due to the Christmas holidays. Gender and ethnicity are not controlled for, because time-invariance forbids the estimation of their coefficients.

2.3.4 Data Cleaning and Overview

The following selection criteria (data cleaning) are applied: First, I verify that there are no double-counts in id-variables. Second, only people aged between 18 and 90 years are included. Only a handful of observations were outside that range and were excluded since they might distort the main conclusions. Third, in line with Zeldes (1989) I eliminate questionable consumption observations, in which consumption grows by more than 300 percent or declines by more than 66 percent per month. Stronger consumption changes are probably due to reporting errors. Keep in mind that irregular, big ticket purchases are excluded and cannot be responsible for strong consumption fluctuations. Entries with negative values for consumption, or consumption categories are dropped, because negative consumption makes no sense. I also delete observations where the sum of food & beverage at home and dining out is below 100 US-dollars. The rationale is that people must eat something and values below 100 US-dollars are probably input errors. Finally, I eliminate extreme, non-representative consumption and income values that lie outside the upper 99.9 percentile.

Tables 2.2 and 2.3 presents summary statistics for the continuous and categorical variables, respectively. The data set covers more than 4,000 individuals. It is an unbalanced panel with different time series support per individual. At best, there are 48 consecutive time waves per individual (on average about 18 observations per individual). Compared to other panel studies on SWB, the time series support of this data set is relatively long. The response rates for the variables of interest are very high. Thus, I do not expect significant bias due to item non-response. The survey designers intended a representative sample of US individuals. People were asked to participate and did not self-select themselves. This mitigates worries about endogenous sample selection. Nevertheless, a small endogenous component remains, since people still accept to be part of the sample. But clearly, this is a concern in any type of survey data and equally applies to every experimental study. The potential attrition bias is less severe for individuals than for firms. If firms leave a panel due to bankruptcy, they basically "die". If people leave the panel, they are likely still alive and simply stop participating. If this non-participation is unrelated to the unobserved component, and not confined to specific sub-populations, this is no problem.

Table 2.2: Summary Statistics – Continuous Variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
C-total	2.670	1.667	0	24.603	86925
C-basic	1.663	1.106	0	17.731	86925
C-conspicuous	1.007	0.855	0	14.700	86925
C-materialistic	2.442	1.540	0	22.625	86925
C-experietial	0.228	0.277	0	4.415	86925
food & beverage (home)	0.373	0.241	0	2.250	86085
health care (out-of-pocket)	0.145	0.286	0	5.088	86925
utilities & housing	0.550	0.409	0	4.165	86925
mortgage	0.675	0.851	0	13.45	80731
personal care & clothing	0.143	0.185	0	2.700	86925
household products	0.046	0.075	0	1.275	86925
car-related	0.196	0.279	0	3.500	79796
gasoline	0.200	0.150	0	1.450	85627
household services	0.039	0.113	0	2.375	86925
child education	0.086	0.496	0	14	86925
care child & elderly	0.060	0.187	0	2.750	86925
sport	0.022	0.085	0	1.800	77672
dining out	0.145	0.157	0	1.577	84593
leisure & entertainment	0.067	0.154	0	2.865	86925
work income (gross)*	2.369	3.591	0	63.900	77082
age	51.799	14.651	18	90	86925

All values for consumption and income are measured in 1,000 US dollars. * Work income is set to zero if people report unemployment, which explains the low mean value. The mean of work income, conditional on being greater than zero, is 3,712 US dollars.

Table 2.3: Summary Statistics – Categorical Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
life satisfaction	3.750	0.854	1	5	85080
happiness	3.336	1.025	1	5	85037
depression	1.821	0.809	1	5	83136
subjective health	3.418	0.908	1	5	85068
wornout	2.750	1.168	1	6	85046
sleep issues	2.051	0.856	1	5	85059
family size	0.986	1.367	0	10	86921
credit card debt	0.293	0.621	0	5	86925
education	4.049	1.572	1	8	86922
state residence	25.016	14.776	1	52	86921
stocks	0.300	0.458	0	1	86360
home owner	0.745	0.436	0	1	83199
health coverage	0.886	0.318	0	1	82997
male	0.416	0.493	0	1	86925
working	0.550	0.497	0	1	86925
self-employed	0.096	0.294	0	1	86925
retired	0.231	0.421	0	1	86925
married	0.669	0.471	0	1	86925
white	0.893	0.309	0	1	86925
black	0.057	0.232	0	1	86925
native	0.006	0.075	0	1	86925
asian	0.017	0.128	0	1	86925
other	0.028	0.164	0	1	86925

Variables coded with minimum 0 and maximum 1 are dummies. Family size: people in addition to the respondent. Education: 1 = no high school graduate, 2 = high school graduate, 3 = college experience without degree, 4 = college degree, 5 = bachelor, 6 = master, 7 = professional school, 8 = doctorate. Credit card debt in US dollars: 1 = (debt $<$ 10,000), 2 = (10,000 $\leq$ debt $<$ 50,000), 3 = (50,000 $\leq$ debt $<$ 100,000), 4 = (100,000 $\leq$ debt $<$ 250,000), 5 = (debt $\geq$ 250,000).

2.4 Econometric Model

2.4.1 Linear Model

Let subjective well-being, SWB_{it}, be the dependent variable, where i denotes the individual and t denotes time. Consumption, C_{it}, denotes the independent variable. Then, the simplest possible model is given by

$$SWB_{it} = \alpha_0 + \alpha_1 C_{it} + u_{it}, \tag{2.1}$$

where α_0 is a constant and u_{it} denotes the error term. The error term captures the respondents inability to communicate actual well-being perfectly correct. It also captures the fact that only discrete responses are allowed. People might, for instance, be uncertain whether to report a 4 (happy) or 5 (very happy), because they feel somewhere in between. Then, the error term reflects that the person must decide to round up or down.

A more realistic model contains further explanatory variables, or taste shifters. These regressors and their corresponding coefficient vector are given by X_{it} and β, respectively. This can be estimated by the following multivariate linear regression:

$$SWB_{it} = \alpha_0 + \alpha_1 C_{it} + X'_{it}\beta + u_{it}. \tag{2.2}$$

This leads to an important econometric point. Cross-sectional data ignore unobserved heterogeneity between individuals, such as personality traits and hormonal routines. In general this leads to inconsistent estimates.[21] In order to exploit the advantages of panel data, the model can be further generalized. In particular, the error term u_{it} can be decomposed into three elements: individual effects, η_i, time effects, θ_t, and an idiosyncratic error term, ε_{it}. This leads to the following equation:

$$SWB_{it} = \alpha_0 + \alpha_1 C_{it} + X'_{it}\beta + \eta_i + \theta_t + \varepsilon_{it}\ . \tag{2.3}$$

I assume that the idiosyncratic error term has zero mean (a constant is included) and variance, σ^2_ε. The time effects can be handled by time dummies. The individual effects

[21] Studies show that inherited elements determine a great part of an individual's SWB-range (Weiss et al. (2008)). These are mainly personality traits (extroversion, neuroticism, openness, conscientiousness, agreeableness, self-confidence, optimism, etc.) and activation or stimulation routines of hormones that regulate happiness, anxiety, and depression (serotonin, dopamine, phenylethamine, endorphins, noradrenalin, oxytocin, ghrelin, etc.).

represent unobserved heterogeneity and are assumed time-constant. The individual effects can be addressed by first-differencing (FD-estimator) or time-demeaning (FE-estimator). Estimating model (2.3) with the FD-estimator or FE-estimator yields consistent estimates if the explanatory variables are exogenous.

2.4.2 Ordered Choice Model

For simplicity, only the linear regression framework was presented so far. As mentioned in the data section, the dependent variable (SWB) is ordinal. This means SWB contains only a few, ordered, and discrete values. In such cases, an ordered choice model constitutes a non-linear refinement to the above-mentioned linear regression methods.

The econometric literature names four major concerns for using the linear probability model (LPM), when the dependent variable is ordinal, or categorical. First, the error term is not normally distributed, which violates the standard LPM assumptions, and the support of its distribution depends on the regressors. Second, the error-variance is heteroskedastic. Both characteristics reduce efficiency and lead to invalid hypothesis tests. Third, in the LPM, a one unit increase of the independent variable has a constant effect on the dependent variable over the whole range of values. In general, a varying impact of the explanatory variable is expected along the distribution (e.g., diminishing returns) — a feature that is better captured by non-linear models. Fourth, the LPM makes nonsensical out-of-bound predictions. In particular, it can predict values that lie outside the bounds that the data dictates.

The ordered choice model is given by

$$P(SWB_{it} \leq y | Z_{it}; \phi) = \Phi(-Z'_{it}\phi) \qquad y = 1, ..., J-1, \tag{2.4}$$

where $P(SWB_{it})$ is the probability of SWB taking on a certain value, conditional on the explanatory variables, Z_{it}. The corresponding coefficient vector is given by ϕ. Φ denotes the cumulative density of the standard normal distribution, which results in a specific ordered choice model, namely, the ordered probit model. Alternatively, the logistic distribution could be used, which would correspond to an ordered logit model.[22] Z_{it} contains a category-specific constant term. J denotes the number of outcomes that the dependent variable (SWB) can take on. Since probabilities add up, $P(SWB_{it} \leq y | Z_{it} = 1)$, only J-1 cut-off points (category-specific constants) can be estimated. Equation (2.4)

[22] The logistic distribution and the corresponding ordered logit model is less attractive than the ordered probit model because no simple estimators are available (Wooldridge (2002)). The normal distribution has the nice property that linear combinations of normal distributions are also normally distributed, which facilitates the estimation via ordered probit.

ignores time and individual effects. As in the linear model, time effects can be handled by time dummies. For facility of inspection, I ignore time effects in the remaining equations, without loss of generality. The subsequent model accounts for unobserved heterogeneity

$$P(SWB_{it} \leq y|Z_{it}, \eta_i; \phi) = \Phi(-Z'_{it}\phi - \eta_i), \tag{2.5}$$

where η_i denotes the individual effects. It is not possible to mimic the linear procedures of first-differencing or fixed-effect transformation in order to eliminate the individual effects. Equation (2.5) assumes that the explanatory variables, Z_{it}, are strictly exogenous conditional on η_i, which, for instance, rules out lagged dependent variables. In equation (2.5), I also assume that the outcome of SWB is independent, conditional on the explanatory variables and fixed effects.

If the relationship between η_i and Z_{it} is not specified and fixed effects are treated as parameters to be estimated, the model suffers from an incidental parameter problem. The incidental parameter problem arises, because the number of fixed effects parameters, η_i, is increasing with the number of individuals (cross-sectional units). Hence, the estimation of η_i is inconsistent, especially if time series observations are very small and the number of cross-sectional units is large. The inconsistency is not limited to the individual effects, but extends to all coefficients, ϕ.

One way to proceed is to assume that the individual effects are uncorrelated with the other explanatory variables, which corresponds to a random effects ordered probit model. But, this assumption is very strong. If there is a relationship between η_i and Z_{it}, and this relationship is ignored, the estimates will be biased. I allow for a correlation between individual effects and explanatory variables, as proposed by Mundlak (1978) and Chamberlain (1980). In particular, Mundlak models the individual effects as follows

$$\eta_i = \overline{Z}'_i\gamma + \epsilon_i \ , \tag{2.6}$$

where $\overline{Z}_i$ represents the time-average of the explanatory variables and γ the corresponding coefficient vector. Conditional on the controls, the error term is normally distributed: $\epsilon_i|Z_{it} \sim$ normal $(0, \sigma^2_\epsilon)$. Plugging equation (2.6) into equation (2.5) gives:

$$P(SWB_{it} \leq y|Z_{it}, \overline{Z}_i, \epsilon_i; \phi, \gamma) = \Phi(-Z'_{it}\phi - \overline{Z}'_i\gamma - \epsilon_i) \ . \tag{2.7}$$

Including the time-averages as controls for the individual effects is very intuitive: it allows to estimate the effect of changing Z_{it}, while holding the time-average fixed. The model

can be consistently estimated by pooled ordered probit. For valid inference, the standard errors should be made robust to arbitrary time dependence.[23] As in the linear model, time-invariant variables should be dropped.

2.4.3 Potential Econometric Issues

One potential problem is that consumption and SWB might be jointly determined. This would make consumption endogenous in equation (2.7), which generally leads to inconsistency. Put differently, it is possible that people with higher SWB behave differently than people with lower SWB. Guven (2012) find that ignoring simultaneity of happiness and consumption leads to downward bias. This implies that the causal effect is, if anything, stronger than the correlative coefficient suggests.[24]

In order to make causal statements about the consumption-SWB relationship it is imperative to test for endogeneity of consumption. Endogeneity tests hinge on finding appropriate instrumental variables (IVs). It turns out difficult to find external instruments, because nearly every variable can be thought of as directly relevant for the SWB equation. If a variable cannot be excluded from the main equation, it cannot serve as a valid IV. Nevertheless, it is possible to use "internal instruments", which are constructed from lagged consumption and lagged polynomials of consumption.

Testing for endogeneity is extremely difficult in ordered choice models. One way to proceed is to ignore the endogeneity issue and access its magnitude from the linear IV model. This can be done if the endogeneity bias is relatively small and its sign is clear. Alternatively, a two-stage routine can be applied as in the linear case: In the first stage, the predicted value for consumption is determined like in the linear model. In the second stage, this predicted value enters the ordered probit model. I rely on the results of linear IV methods, which are more robust. The literature on endogeneity treatments in ordered choice models is not fully developed yet. A formal treatment of endogeneity and the corresponding IV regressions (conducted in the linear model) is performed in section 5.3.

[23] The model with included time-averages can also be estimated with random effects ordered probit, which is more efficient. All coefficients must be scaled by $(1 + \sigma_\epsilon^2)^{-0.5}$.

[24] The same problem might apply to income. Previous literature, however, suggests that for income this issue is only relevant for medium-term dynamic relations. In other words, people with higher SWB do not instantly earn more, but might benefit financially some years ahead (De Neve and Oswald (2012)). One could also argue that wages are unlikely to react to short-term variation in SWB, because wages are sticky (due to legal contracts). Since the present data set covers monthly data and focuses on contemporaneous relationships, simultaneity between income and SWB can be ignored.

2.4.4 Interpretation of Ordered Probit Coefficients

The ordered probit coefficients cannot be interpreted as easily as the coefficients in the linear model. I sketch a few possibilities for interpretation, but focus on one particular interpretation, which is very straightforward in the current context.

First, it is possible to interpret only the sign and the significance of the coefficients. This is a particularly useful way to compare ordered choice regression outcomes to linear regression outcomes. The drawback is that the sign conveys little information. Second, one can compute marginal probabilities (MP), which are defined as the derivative of the probability function. Afterward, the average over all individual marginal probabilities is computed — called the average partial effect. Third, it is possible to compute the marginal probabilities evaluated at a specific value. Commonly, the sample-average is used. Hence it is called the partial effect at the average. The second and third interpretation are similar and share a common drawback. For ordered choice models, the marginal probabilities must be computed for every possible value that the dependent variable can take on. Thus, the interpretation can become very cumbersome.

Finally, trade-off ratios, which evaluate the importance of one explanatory variable relative to another explanatory variable, can be used. This interpretation is very handy for the current analysis, since the consumption and income variables use the same measurement unit — 1,000 US dollars — which facilitates relative comparisons among them. The technique, however, works also for different measurement units. The question is how much variation in one explanatory variable is needed to offset the change in another variable while holding the outcome probability of the dependent variable constant. Hence, the concept of the trade-off ratios corresponds to the ratio of coefficients in the ordered probit model. One example: If the coefficient for regressor A is 0.05 and the coefficient for regressor B is 0.2; the ratio $B/A = 0.2/0.05 = 4$. This means that a one unit increase in regressor B must be offset by a four unit reduction in regressor A to keep the outcome probability of the dependent variable unchanged. In this way, it becomes fairly easy to evaluate regressors relative to each other. For a formal derivation see Boes and Winkelmann (2010).

2.5 Results

2.5.1 Main Results

In the remainder, consumption and income are measured in 1,000 US dollars. Due to the large number of observations, a relatively high estimation accuracy can be expected. Thus, I limit the discussion of statistical significance to the 1 percent (indicated by

three stars ***) and 5 percent level (indicated by two stars **) and ignore moderate significance at the 10 percent level (indicated by one star *). All subsequent regression tables have a similar format. There are three dependent variables, which represent different constructs of SWB: in the first column life satisfaction (LS), in the second column happiness (H), and in the third column depression (D). The control variables are the same across all specifications. Table 2.4 shows the regression results for the ordered probit model, according to equation (2.6).

Table 2.4: Consumption and SWB – Ordered Probit

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
Financial Situation			
consumption	0.0447***	0.0315**	-0.0198
	(0.0134)	(0.0125)	(0.0126)
consumption^2	-0.0016	-0.0011	0.0005
	(0.0010)	(0.0010)	(0.0010)
income	0.0087***	0.0015	-0.0019
	(0.0020)	(0.0015)	(0.0020)
stocks	0.0353**	0.0360**	-0.0063
	(0.0178)	(0.0173)	(0.0187)
credit card debt	-0.0352***	-0.0299***	0.0277***
	(0.0101)	(0.0090)	(0.0095)
home owner	0.0415	-0.0218	0.1118***
	(0.0386)	(0.0405)	(0.0413)
health insurance	0.1038***	0.0100	-0.0378
	(0.0366)	(0.0359)	(0.0337)
Health			
health (1-5)	0.2969***	0.2358***	-0.2003***
	(0.0141)	(0.0125)	(0.0138)
wornout (1-5)	-0.1275***	-0.2045***	0.2304***
	(0.0077)	(0.0087)	(0.0086)
sleep issues (1-5)	-0.1567***	-0.2109***	0.3780***
	(0.0094)	(0.0101)	(0.0120)
Demographics			
age	0.1262**	0.0389	-0.0368
	(0.0592)	(0.0587)	(0.0648)
age^2/100	-0.3418***	-0.1289	0.1126

	(0.1156)	(0.1164)	(0.1283)
age^3/10000	0.1718**	0.0948	-0.0674
	(0.0729)	(0.0739)	(0.0817)
family size	-0.0415***	-0.0064	0.0210*
	(0.0129)	(0.0118)	(0.0124)
working	0.2180***	0.1267***	-0.1789***
	(0.0263)	(0.0239)	(0.0253)
self-employed	0.0875**	0.0684*	-0.0989**
	(0.0442)	(0.0416)	(0.0418)
retired	0.0976**	0.0971**	-0.1404***
	(0.0407)	(0.0417)	(0.0387)
married	0.3404***	0.2861***	-0.3705***
	(0.0530)	(0.0536)	(0.0554)
education	-0.0179	0.0102	0.0207
	(0.0376)	(0.0364)	(0.0419)
US-State	0.0022	-0.0020	0.0004
	(0.0035)	(0.0034)	(0.0031)
Time-Average of Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
Pseudo R-squared	0.1478	0.1739	0.2263
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-72988	-77248	-63745

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, time-averages of controls, and time effects are not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Consumption has a significant positive effect on LS and H, but is insignificant and negative for D. The coefficient on squared consumption is insignificant. Income is only significant (positive) for LS. Boes and Winkelmann (2010) find contradicting evidence, namely that income reduces dissatisfaction, but has no impact on satisfaction. Their findings can be explained by their interpretation of dissatisfaction and satisfaction. For them, dissatisfaction is a low value on the life satisfaction scale, whereas satisfaction is the positive end of the life satisfaction scale. Having distinct constructs for positive and negative well-being — as in this study — draws a more accurate picture. The consumption coefficient is about five times as large as the income coefficient. Stock ownership increases LS and H, whereas credit card debt lowers SWB. Home ownership

has no significant influence on LS and H. Somewhat surprisingly, it significantly increases D. This might be due to the associated long-term financial burden through interest and down payments. Health insurance increases LS, most likely, by satisfying security needs. Overall, the financial situation is significantly related to SWB. Self-evaluated health; including physical health, worn-out syndromes, and sleep issues; is highly significant and very sizable. Better physical health improves SWB; being worn-out and having sleep issues reduces SWB. Age is only relevant for LS, suggesting an N-shaped pattern over the life-cycle. The emotional states, H and D, are unaffected by age. Family size lowers LS. Employment and marriage have a significant, sizable, and positive effect on all three constructs of SWB. This finding conforms well to the existing literature. In addition, the type of work matters. Self-employed people are more satisfied, happier, and less depressed. Reaching retirement is also positively associated with all three constructs of SWB. Education and the US-state of residence are insignificant.

Let me stress three important points. First, LS has more significant covariates than H and D. This makes sense, since LS is the broad cognitive evaluation of life, whereas H and D only capture short-lived emotions. Second, and closely related, it pays to disentangle cognitive and affective components of SWB. As was shown, the significance and strength of covariates varies for LS, H, and D. Third, although the financial situation matters, the three strongest predictors of SWB are marriage, perceived physical health, and employment.

To facilitate the interpretation of the results, I discuss a few examples of coefficients in the first column (LS). The trade-off between different coefficients can be analyzed in form of a compensation scheme. Remember that one unit of consumption corresponds to 1,000 US dollars. The coefficient on consumption is 0.045. The coefficient for marriage is 0.340, which is more than seven times larger ($7 \times 0.045 = 0.315 < 0.340$). Other things equal, the privilege of marriage is worth more than 7,000 US dollars per month. Although this number seems strikingly high, it is in line with previous research. Blanchflower and Oswald (2004) estimate that a lasting marriage is worth 100,000 US dollars of income per year. Another example is the coefficient on retirement (0.098), which is about twice the coefficient on consumption (0.045). Hence, being retired is worth 2,000 US dollars per month in terms of SWB. These compensation considerations are only suggestive. Clearly, not everyone can forgo these amounts of money, or would actually realize these compensations.

The results confirm hypothesis 1, which states that consumption is positively associated with SWB. Hypothesis 2, which states that consumption primarily influences the emotional parts of well-being, but not cognition, is rejected. In fact, consumption has the strongest association with LS.

Table 2.5 shows the regression on two consumption types: basic consumption and conspicuous consumption. The same controls as before are used, but are not reported for clarity of exposition. Conspicuous consumption is highly significant and positively associated with SWB, whereas basic consumption is insignificant and close to zero. Numerically, the size of the conspicuous consumption coefficient is about the same as the total consumption coefficient in table 2.4. This suggests that in the United States the total consumption effect stems mainly from conspicuous consumption. Most likely, because the majority of people have already crossed the point of basic need satisfaction. The results confirm hypothesis 3, which states that conspicuous goods have a stronger association with SWB than basic goods.

Table 2.5: Basic vs. Conspicuous Consumption – Ordered Probit

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-basic	0.0048	0.0080	0.0020
	(0.0096)	(0.0086)	(0.0090)
C-conspicuous	0.0434***	0.0287***	-0.0248***
	(0.0091)	(0.0080)	(0.0088)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
Pseudo R-squared	0.1480	0.1738	0.2262
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-72973	-77253	-63748

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6 presents the results for materialistic and experiential consumption types. Materialistic consumption has a small, but significant effect on LS. Experiential consumption is highly significant and much more sizable for all three constructs of well-being. Note the asymmetric effect of consumption on positive and negative states of SWB: consumption is better suited to improve positive well-being than to alleviate bad moods. The results confirm hypothesis 4, namely that experiential consumption is stronger associated with SWB than materialistic consumption. A potential reason is that experiential consumption constitutes only 8.5 percent of total consumption, whereas materialistic consumption constitutes a major share of total consumption. It is possible that the

difference between experiential and materialistic coefficients narrows once people increase their relative expenditure of experiential goods. Put differently, if you travel all year long, you might get accustomed to this high standard of living in the same way as you adapt to possessions. However, this possibility is only speculative and more research is needed.

Table 2.6: Materialistic vs. Experiential Consumption – Ordered Probit

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-materialistic	0.0161**	0.0105*	-0.0064
	(0.0067)	(0.0058)	(0.0061)
C-experiential	0.1251***	0.1126***	-0.0777***
	(0.0240)	(0.0210)	(0.0247)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
Pseudo R-squared	0.1485	0.1741	0.2262
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-72931	-77229	-63746

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Consumption Categories and SWB – Ordered Probit

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
food and beverage (home)	0.0583*	0.0266	-0.0287
	(0.0336)	(0.0323)	(0.0370)
health care (out-of-pocket)	-0.0428**	-0.0354**	0.0319*
	(0.0170)	(0.0165)	(0.0170)
utilities and housing	0.0331	-0.0110	-0.0057
	(0.0270)	(0.0243)	(0.0272)
mortgage	0.0180	0.0228	-0.0186
	(0.0174)	(0.0161)	(0.0164)
personal care and clothing	0.1554***	0.1101***	-0.0670*
	(0.0368)	(0.0304)	(0.0348)

household products	0.0456	0.1360*	-0.1435*
	(0.0669)	(0.0701)	(0.0745)
household services	-0.0155	-0.0620	0.0624
	(0.0574)	(0.0481)	(0.0576)
car-related	-0.0350	-0.0198	-0.0000
	(0.0398)	(0.0356)	(0.0400)
gasoline	0.0549	0.0780	-0.0085
	(0.0577)	(0.0536)	(0.0595)
child education	0.0246**	0.0059	-0.0118
	(0.0108)	(0.0091)	(0.0105)
care child and elderly	-0.0005	-0.0370	0.0715**
	(0.0315)	(0.0295)	(0.0331)
sport	0.1322**	-0.0110	-0.0217
	(0.0552)	(0.0517)	(0.0673)
dining out	0.1292**	0.1418***	-0.0748
	(0.0519)	(0.0482)	(0.0541)
leisure and entertainment	0.0714**	0.1144***	-0.0541
	(0.0332)	(0.0306)	(0.0353)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	62978	62977	62980
Pseudo R-squared	0.1519	0.1778	0.2285
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-62196	-65940	-54409

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7 presents results when consumption is disaggregated into 14 consumption categories. Only seven categories have a significant impact on SWB (not counting the 10 percent significance level). Six consumption categories are significant for LS: health care, personal care & clothing, child education, sport, dining out, and leisure & entertainment. Four consumption categories are associated with happiness: health care, personal care & clothing, dining out, and leisure & entertainment. Health care consumption expenditure is probably negatively associated with SWB, as it goes hand in hand with worse health. Note that health variables are controlled for, so there is no omitted variable problem. People are punished twice for bad health; directly through their suffering and indirectly

through increased financial costs. Money spent on care for children and elderly is the only consumption category that is significantly associated with depression; it increases depression. LS is associated with the most consumption categories, confirming that it is the broadest construct of SWB. Surprisingly, personal care & clothing, which is classified as materialistic, has a larger coefficient than all experiential categories for LS. The coefficients of the other explanatory variables (not reported) do not change compared to previous tables.

Hypothesis 5 predicts that dining out, leisure & entertainment, and sport expenditures, should have the strongest impact on SWB. This can be partly confirmed. All three belong to the four categories with the strongest association with LS. Dining out and leisure & entertainment belong also to the three categories with the strongest association with H. Only sport expenditure is non-significant in the happiness equation. Sport expenditures might not have an instantaneous effect on emotional well-being (happiness), but rather deliver long-term benefits (life satisfaction), for instance, through better health and appearance.

2.5.2 Robustness Checks

2.5.2.1 Estimation Technique

This section explores whether the results are sensitive to the selected estimation model (ordered probit, equation (2.7)). Tables A.1 and A.2 present the linear fixed-effects regression model for total consumption and consumption categories, respectively. This corresponds to estimating equation (2.3). The results are robust to model specification. As before total consumption is significantly associated with LS and H, but not D, and income is only significant for LS. It turns out that the linear specification favors additional significant consumption categories: food & beverage at home and car-related expenses for LS, and household products for H. Otherwise, the results are widely unaffected.

2.5.2.2 Consumption Ratios

So far, the different consumption categories entered the regression in level form. It is possible that results differ if consumption ratios are used. Consumption ratio means that a particular consumption category is divided by total consumption (e.g. food and beverage divided by total consumption). Then, the consumption ratio reflects the percentage share of the particular consumption category relative to total consumption. Table A.3 shows that the main conclusions remain widely unaffected.

2.5.2.3 Variation in Control Variables

Until now, all regressions contained income as control variable. The main rationale for doing so, is that the impact of consumption, consumption types, and consumption categories might vary for different income groups. Table A.4 shows that excluding income from the regressions does not change the main results. Furthermore, some people might argue that subjective explanatory variables should be excluded, because their assessment is simultaneously determined with the subjective dependent variable, and hence, they might affect each other. Therefore, I re-run the regression without physical health, worn-out, and sleep issues — all three are measured subjectively. Table A.5 indicates that the relevant consumption categories are essentially unaffected. For some consumption categories, significance drops by one star (*). On the other hand, the coefficient on health care is now also highly significant for depression. This is not unexpected, since health care spending captures direct (physiological suffering) and indirect (additional required costs) consequences of bad health now that health controls are excluded.

2.5.2.4 Categorization of Consumption Types

Tables A.6 and A.7 investigate the robustness of the categorization of the consumption types. Details on the categorization are given in Appendix A. For the robustness of basic and conspicuous consumption a more restrictive categorization is chosen for conspicuous consumption. That means, less consumption categories are declared conspicuous. In table A.6 conspicuous consumption remains significant and is twice the size as before (table 2.5) for all three constructs of SWB. Basic consumption has a small but significant coefficient in the LS equation. Table A.7 shows that experiential consumption remains highly significant for SWB, whereas materialistic consumption is insignificant. The size of the coefficients does not change significantly compared to table 2.6. Overall, the result that experiential (conspicuous) consumption is more important than materialistic (basic) consumption is robust.

2.5.3 Addressing Potential Endogeneity and Causal Inference

So far, the results emphasized empirical regularities and avoided statements about causality. One issue is that consumption might be endogenous due to joint determination with SWB. This section uses instrumental variables (IVs) for consumption in order to provide causal inference. At the same time, I test for endogeneity to see whether IV estimation is even necessary. A good IV has two properties: *validity* and *relevance*. Validity means that the instrument is uncorrelated with the error term and not part of the original equation. Relevance means that the instrument is (sufficiently) correlated

with the endogenous variable, in order to explain its variation.

The over-identification test (Hansen-J) can be used to evaluate the *validity* of the instruments. Its null hypothesis is that instruments are valid, which means uncorrelated with the error term. All tests are evaluated at the 5 % significance level. The *relevance* of IVs is examined by three test statistics: Shea's partial R-squared, an under-identification test, and a weak identification test. Shea's partial R-squared essentially gives the R-squared once all included explanatory variables have been partialled out. In other words, it measures the explanatory power of the excluded instruments, alone. I use cluster-robust standard errors for all regressions, which means I need test statistics that are robust to errors that are not independently identically distributed. The Kleibergen-Paap LM test is used for the under-identification test (null hypothesis: under-identification) and the Kleibergen-Paap Wald statistic (null hypothesis: weak identification) is used to access weak identification. Finally, to test for endogeneity, a robust version of the Durbin-Wu-Hausman test is applied. The null hypothesis is exogeneity.[25]

Due to the lack of external IVs (variables that are not part of the considered equations), I employ lagged polynomials of consumption as internal IVs. As mentioned in section 4.3, I use linear IV methods, because ordered choice IV methods are extremely complex and not fully developed yet. Particularly, I use the fixed effects two-stage least square model. First, I eliminate the individual fixed effects by time-demeaning. Second, I instrument time-demeaned consumption by time-demeaned lagged polynomials (1-4) of consumption.

In table 2.8, IV estimation and endogeneity testing is conducted for consumption and squared consumption. The corresponding first-stage regressors are given in table A.9 Consumption is insignificant for LS and D, but sizable and significant for H. But is it even necessary to use IV methods? IV methods should only be used when a regressor's suspected endogeneity cannot be rejected with sufficient certainty. After all, IV standard errors are wider than standard errors in the non-instrumented equations, and hence, less significant results are expected for IV estimates. First of all, the over-identification tests do not reject instrument validity (p-value LS: 0.5074; H: 0.3479; and D: 0.1383). Second, the relevance of the chosen IVs is supported. Shea's partial R-squared of the first-stage regression is 0.0992 for consumption and 0.0608 for squared consumption. Additionally, the Kleibergen-Paap LM statistic (under-identification) is 105.574 for LS, 105.585 for H, and 105.305 for D. For all three dependent variables the p-value is 0.0000, and hence, rejects under-identification. Furthermore, weak identification is also unlikely when comparing the Kleibergen-Paap Wald statistics (47.586, 47.586, and 47.496, respectively)

[25] The general idea of the Durbin-Wu-Hausman test involves four steps: First, the reduced form equation is estimated. Second, the residuals of this equation are saved. Third, the residuals enter the original equation of interest. Fourth, it is evaluated whether the residuals are significant. If the residuals are statistically significant this hints at endogeneity.

to the critical values of Stock-Yogo, 11.04. The test statistics are larger than the tabulated values for the 5% maximal IV relative bias. Taken all test statistics together, the instruments are found to be valid and relevant (having considerable explanatory power). The null hypothesis of the endogeneity test is that consumption and squared consumption are exogenous. I fail to reject exogeneity for all three equations. The p-values of the endogeneity test are 0.6243 (LS), 0.0990 (H), and 0.6863 (D), respectively. Hence, it is relatively safe not to instrument consumption in these equations and to rely on table 2.4 for causal estimates.

Table 2.8: Causality – Linear Fixed-Effects IV-Estimation

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
consumption	0.0379	0.0810***	-0.0298
	(0.0271)	(0.0281)	(0.0227)
consumption^2	-0.0031	-0.0072**	0.0026
	(0.0026)	(0.0030)	(0.0025)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	60506	60506	60510
R-squared	0.0777	0.0942	0.1226
P-Value Wald-Test	0.0000	0.0000	0.0000
P-Value Endogeneity Test	0.6243	0.0990	0.6863
P-Value Hansen-J	0.5074	0.3479	0.1383

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects accounted for, but not reported.

First-stage instruments: lagged consumption polynomials 1 to 4.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8 shows ordered probit regressions on different domains of satisfaction (context-specific), which are parts of total life satisfaction. It lends further support for a causal direction of consumption on life satisfaction. Moreover, it suggests through which channels consumption drives life satisfaction. Both, consumption and income have a significant, positive impact on income satisfaction, economic satisfaction, and job satisfaction. Consumption has a stronger impact than income. Consumption and income have no impact on social and family satisfaction and health satisfaction. Admittedly, this might also be due to the much lower sample size for these two variables. The

consumption and income coefficients give a causal direction, as it is unclear why income satisfaction, economic satisfaction, or job satisfaction should affect contemporaneous consumption (or income). Even if low income satisfaction, economic satisfaction, or job satisfaction would induce behavioral changes in subsequent periods, this paper emphasizes the contemporaneous relationship of consumption and SWB. Hence, no estimation bias is expected. Easterlin (2006) shows that a weighted aggregation of domain satisfactions predicts overall life satisfaction very well. If consumption and income causally affect domains of life satisfaction, they are also likely to affect total life satisfaction causally.

Table A.10 shows linear IV regressions and tests for endogeneity in the two suspected variables: basic and conspicuous consumption. Table A.11 presents the corresponding first-stage regressions. Basic consumption is insignificant. Conspicuous consumption is slightly significant (10 % level) for LS, highly significant for H, and insignificant for D. The size of the coefficients does not significantly differ from the non-instrumented linear estimates in table A.12, considering the 95 percent confidence interval. Instrument validity is not rejected, considering the Hansen-J test. Also, the instruments are not rejected as relevant: Shea's partial R-squared of the first-stage regression is 0.1763 for basic consumption and 0.068 for conspicuous consumption. Under-identification is rejected via the Kleibergen-Paap LM test. The under-identification test is 442.336 for life satisfaction; 442.944 for happiness; and 442.564 for depression (p-value: 0.0000). Weak identification is also unlikely. The Kleibergen-Paap Wald statistic are 118.726, 118.996, and 118.808, respectively; all being greater than the Stock-Yogo critical value of 17.70 for 5% maximal IV relative bias. The endogeneity does not reject the null of exogeneity for basic and conspicuous consumption (LS: 0.6728, H: 0.1983, D: 0.7043 $>$ 0.05). Thus, it is not necessary to instrument the two consumption types.

Table A.13 shows linear IV regressions and tests for endogeneity in the two suspected variables: materialistic and experiential consumption. Table A.14 contains the corresponding first-stage regressions. Materialistic consumption is insignificant. Experiential consumption, however, is highly significant and several times stronger than in the non-instrumented linear estimation; see table A.15. Evaluating the 95 percent confidence interval, the difference between instrumented and non-instrumented coefficients is also significant. The over-identification test does not reject instrument validity (p-values: 0.0683, 0.0906, 0.3609 $>$ 0.05). Now, I turn to the question of instrument relevance. Shea's partial R-squared of the first-stage regression is 0.1219 for materialistic consumption and 0.0244 for experiential consumption. Additionally, under-identification is rejected via the Kleibergen-Paap LM test. The under-identification test is 339.283 for LS; 339.221 for H; and 339.282 for D. For all three dependent variables the p-value is 0.0000, and hence, rejects the null that the model is under-identified. Furthermore, weak

identification is also unlikely when comparing the Kleibergen-Paap Wald statistic to the critical values of Stock-Yogo: the weak identification test statistics are 68.235, 68.214, and 68.227, respectively. All values are greater than 17.70, the value for the 5% maximal IV relative bias. In a nutshell, the results favor instrument validity and relevance. For LS (p-value: 0.004) and H (p-value: 0.0036), I reject the exogeneity of materialistic and conspicuous consumption at the 5 percent significance level. Therefore, it makes sense to instrument both variables. In conclusion, there is a strong causal effect from experiential consumption on SWB. In fact, the causal effect is much stronger than the correlative effect suggests (table A.15).

2.5.4 Comparison with Other Results

Table 2.9 compares this paper's results to the results of DeLeire and Kalil (2010). The focus lies on three major differences. One difference is the data set that is used. Another difference is the number and assignment of consumption categories. DeLeire and Kalil (2010) use nine consumption categories, whereas I divide total consumption into 14 categories. They use, for instance, leisure as one category that subsumes leisure, sport, and entertainment, whereas I divide it a little further and have sport as an extra category. They also include a durable good category in their analysis, whereas I exclude durable big-ticket items. The third difference is the estimation model. They use an OLS regression on cross-sectional data. I use an ordered choice panel model to account for the ordinal nature of the dependent variable and to address individual heterogeneity bias. In table 2.9, the abbreviations in the header of each column are explained as follows: *tc* = their categorization, *tm* = their model, *mc* = my categorization, *mm* = my model, and *td* = their data. Column 1 shows their baseline results, using their data set, their categorization, and their model. Only leisure is significant. The results in columns 2 to 5 are all based on my data set, but use varying combinations of categorization and model. Column 2 imitates their approach with my data set. An important difference is that personal care goes from insignificant to highly significant. The different data sets — the current data set is much larger — lead to a first significant difference. Column 3 uses their categorization but the ordered probit model for estimation. This leads to two further consumption categories that become significant: health care and dining out. Column 4 uses my consumption categories but their OLS regression.[26] In comparison to column 2, household products are additionally significant. Column 5 shows my baseline results. Clearly, there are stark differences. Particularly, there are many more significant

[26] Their data is cross-sectional and they employ OLS. Since my data set is a panel, I run a linear pooled regression and adjust the standard errors for individual clustering to mimic the method as close as possible.

consumption categories in column 5. Moving from column 1 to 5 shows that the difference in the results comes from a combination of varying data sets, different categorization of consumption goods, and a different estimation model. It is especially important to recognize that the different results do not only stem from assembling the consumption categories differently. There are also differences for the categories that overlap in both studies. Since I use a larger data set, account for fixed individual effects, and use the more appropriate ordered choice model, there is good reason to put stronger belief in my results.

Table 2.9: Consumption Categories and SWB – Comparison to DeLeire and Kalil

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Life Sat	tc/tm/td	tc/tm	tc/mm	mc/tm	mc/mm
food and beverage (home)	0.001	-0.0570	0.0361	-0.0641*	0.0583*
	(0.072)	(0.0373)	(0.0308)	(0.0377)	(0.0336)
health care (out-of-pocket)	-0.055	-0.0325	-0.0361**	-0.0388*	-0.0428**
	(0.078)	(0.0207)	(0.0156)	(0.0214)	(0.0170)
utilities and housing	-0.005	-0.0237*	0.0228	-0.0250	0.0331
	(0.013)	(0.0128)	(0.0142)	(0.0276)	(0.0270)
mortgage	-	-	-	-0.0237	0.0180
	-	-	-	(0.0149)	(0.0174)
personal care and clothing	0.126	0.1626***	0.1165***	0.1481***	0.1554***
	(0.078)	(0.0286)	(0.0244)	(0.0370)	(0.0368)
household products	-	-	-	0.2783***	0.0456
	-	-	-	(0.0812)	(0.0669)
car-related	0.087	-0.0002	-0.0088	-0.0243	-0.0350
	(0.087)	(0.0270)	(0.0319)	(0.0320)	(0.0398)
gasoline	-	-	-	0.0692	0.0549
	-	-	-	(0.0611)	(0.0577)
household services	-	-	-	0.1087*	-0.0155
	-	-	-	(0.0601)	(0.0574)
child education	-	-	-	-0.0033	0.0246**
	-	-	-	(0.0118)	(0.0108)
care child and elderly	-	-	-	0.0388	-0.0005
	-	-	-	(0.0422)	(0.0315)
sport	-	-	-	0.1004*	0.1322**
	-	-	-	(0.0603)	(0.0552)
dining out	0.055	0.1001*	0.1633***	0.0907	0.1292**

	(0.156)	(0.0570)	(0.0464)	(0.0577)	(0.0519)
leisure and entertainment	0.170**	0.0824***	0.0935***	0.0669*	0.0714**
	(0.084)	(0.0306)	(0.0283)	(0.0344)	(0.0332)
Controls	Yes	Yes	Yes	Yes	Yes
Individual Effects	No	No	Yes	No	Yes
Time Effects	No	Yes	Yes	Yes	Yes
Observations	1733	71099	71099	62978	62978
Adjusted R-squared	0.21	0.2944	-	0.2952	-
Pseudo R-squared	-	-	0.1494	-	0.1519
Log-Likelihood	-	-77137	-70506	-68262	-62196
Significance	-	0.0000	0.0000	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.6 Conclusion

This paper looks at the association between specific consumption categories and subjective well-being (SWB). The research question is motivated by two aspects; first, by psychological findings that certain consumption types deliver more well-being than others; and second, by the surprisingly silent economics literature on this topic. It is surprising for at least three reasons. First, well-being is the highest-ranked goal of humanity. Second, people devote considerably efforts to income accumulation, because they see it as a major driver of well-being. But do they put similar efforts into the choice of how to spend their money? Third, there is a vast economic literature on income and SWB, but it does not extend to consumption composition.

The main contribution of this paper is to fill the above-mentioned gap in the economics literature. The only similar approach that I am aware of comes from DeLeire and Kalil (2010). As they point out themselves, their results hinge on a severely limited data set, and consequently also on a restrictive econometric procedure. I improve upon their analysis in five important aspects. First, I use a large representative sample of US individuals, which allows a generalization of results. Second, I employ an ordered choice model to account for the ordinal nature of SWB data. Unlike linear models, ordered choice modeling avoids out-of-bound predictions and increases efficiency. Third, panel data is used, which allows to address unobserved heterogeneity among individuals. Fourth, instrumental variable estimation provides a causal interpretation of the results. Fifth, the

data set provides three different constructs (measures) of SWB, namely, life satisfaction, happiness, and depression. This aids a more accurate understanding of how, and through which channels, consumption goods influence human well-being.

The paper provides four main results. First, consumption is positively associated with SWB. Second, only 7 out of 14 consumption categories are significantly associated with SWB. In contrast, DeLeire and Kalil (2010) find that only leisure consumption affects well-being. Table 2.9 shows in detail were the differences come from. Third, SWB is mainly influenced through experiential and conspicuous consumption, albeit materialistic consumption in form of personal care & clothing has the highest association with SWB. Fourth, instrumental variable estimation and endogeneity tests provide evidence for a causal effect of consumption on SWB. The results hold up to several robustness checks. The insights are probably not limited to the US case and should carry over to other affluent societies.

The results suggest that the decision how to spend money is extremely important. The coefficient for consumption is much larger than the coefficient for income. Hence, income maximization should not be the only monetary concern of human beings. Nevertheless, income remains highly important as it finances consumption. The results simply suggest that it might pay off to shift the focus from sole income accumulation to efficient consumption choice; both for daily routines of individuals and for academic inquiries.

The analysis is subject to certain limitations. The paper focuses on the short-term association of consumption and SWB for individuals. This demand-side focus ignores potential economic benefits on the supply side. There is a powerful case for consumerism: If more products are sold, this yields higher profits for companies (producers), secures jobs, and lowers the burden of the welfare state. Ultimately, this would be beneficial for consumers, as well. Additionally, the current work did not address long-term interrelations (dynamic model), relative consumption, and other time-frequencies. Moreover, it would be interesting to test the consumption-SWB relationship in other affluent societies and in developing, non-affluent countries. Finally, a detailed instrumental variable estimation for the different consumption categories is still outstanding. The aforementioned points are left as an interesting and challenging agenda for future research.

Chapter 3

Relative Consumption: The Strength of Internal and External Habits

3.1 Introduction

This paper investigates the importance of relative consumption preferences. In particular, it estimates the strength of internal and external consumption habits. *Internal habit formation* describes a preference specification, in which the periodic utility function does not only depend on the current consumption level, but also on the "habit stock" that was formed through past consumption. Internal habituation implies that people adapt to consumption over time. Assume that a person consumes 1,000 Euro in period t. Now, assume that the same person consumes 1,000 Euro in the subsequent period, $t+1$, as well. The utility in period $t+1$ is lower, although the same amount is consumed. This happens, because the person adapts to the consumption level, and subsequently needs more consumption to get the same utility (ceteris paribus).[1] *External habit formation* describes a preference specification, in which periodic utility depends (negatively) on the consumption of other people. Ceteris paribus, a person has lower utility if the consumption of others increases. External habits, thus, introduce negative externalities. In fact, external habits are no genuine habits, but rather social reference points. Nevertheless, the words internal and external synchronize terminology and help to distinguish between time-inseparable (own past consumption) and interdependent (consumption of others) consumption preferences. Moreover, they have the same directional impact on utility: given current own consumption, both internal and external habits lower current utility.

The economic literature typically employs a convenient utility representation that

[1] Internal habits capture an important feature of neuroscience. Repetition of a stimulus reduces the perception of the stimulus, which leads to decreased responsiveness. This explains why utility is not only linked to the consumption level, but also to changes in consumption.

ignores habits, although already Smith (1759), Veblen (1899), and Duesenberry (1949) stressed the importance of relative consumption. But, there are also several studies that use the theoretical idea of habit formation to explain important empirical regularities. In utility models with internal habits (time-inseparable), people's adjustment to permanent income shocks is slower, compared to utility models without habits (time-separable). This explains the observed *excess smoothness of consumption* and further *macroeconomic phenomena* in the data (Deaton (1987), Campbell and Mankiw (1989), Carroll and Weil (1994), Shintani (1996)).[2] Habit theory also provides a resolution to the *equity premium puzzle* (Constantinides (1990), Abel (1990), Campbell and Cochrane (1999)).[3] Finally, habit theory can inform industrial organization and marketing research in *dynamic product pricing strategies*. Appendix A.2 provides a more elaborate overview over theoretical, macro-econometric, and micro-econometric papers.

Stimulated by the success of habit theory in explaining the aforementioned regularities, econometricians started to test habit preferences more rigorously. Both macro-econometric and micro-econometric studies, however, provide inconclusive results on the existence, sign, and size of habits. Using aggregate consumption, Dunn and Singleton (1986), Eichenbaum et al. (1988), and Muellbauer (1988) find little evidence of internal habit formation at monthly and quarterly frequencies. Eichenbaum and Hansen (1990), Ferson and Constantinides (1991), and Fuhrer (2000), however, support internal habits at the annual, quarterly, and monthly frequency. Korniotis (2010) finds evidence for external habits, but rejects internal habits, whereas Grishchenko (2010) finds the opposite. Apart from the ambiguous results, the macro-econometric studies leave the micro behavior behind a veil of ignorance. Moreover, they share a common problem. Their findings could stem from serial correlation of aggregate consumption growth, which is probably due to factors unrelated to preferences; for instance, time aggregation, time averaging, and data construction methods. These features render aggregate consumption smoother than individual consumption. Furthermore, aggregate data ignores the importance of individual heterogeneity.

There are two problems with available micro-econometric studies. First, their findings are inconclusive: Carrasco et al. (2005) and Browning and Collado (2007) support habit formation, whereas Meghir and Weber (1996), Dynan (2000), Guariglia and Rossi (2002),

[2] Buraschi and Jiltsov (2007) employ habits to analyze the term structure of interest rates. In addition, habits can account for pro-cyclical stock price variation (Campbell and Shiller (1988)), counter-cyclical variation of stock market volatility (Harvey (1989)), and the equity home bias (Shore and White (2002)). Habit formation is also used to explain business-cycles (Boldrin et al. (2007)), the saving-growth relationship (Carroll et al. (2000)), and the response of consumption to monetary shocks (Fuhrer (2000)).

[3] Intuitively, habits amplify the utility loss that is associated with large and rapid consumption decreases. Therefore, investors require a higher risk-premium (compared to the time-separable utility function) in order to hold risky assets.

and Iwamoto (2011) reject habit formation in favor of durability. The different results of the above-mentioned studies can be explained by different methodology, data, and time frequency. Unfortunately, there is no guidance which of these differences drives the varying results. The second problem is that nearly all micro-econometric studies rely on food consumption data (or narrow sub-categories of household consumption, e.g., tobacco). The main reason is that panel data on total household consumption data was difficult to come by until very recently.[4] As a matter of fact, food constitutes a bad proxy for total household consumption. In particular, Shea (1994) shows that food consumption preferences differ considerably from consumption preferences of other goods. For instance, food represents a major part of a low-income household's budget, but only a small fraction of the budget of a high-income household.[5] In addition, Attanasio and Weber (1995) strongly reject separability between food and other consumption preferences.

To address these issues total household consumption data is used. The RAND American Life Panel (2013) provides monthly information on household consumption expenditures. The paper employs a structural model, in which habits enter the utility function in an additive form. The first-order conditions that arise from the utility maximization lead — after some manipulations — to an econometrically testable Euler equation. Using the aforementioned data set allows to estimate the structural habit parameters. Lagged consumption growth enters the equation as an endogenous regressor. To get consistent estimates, this demands for dynamic panel methods. I use the transformed-GMM estimator (forward orthogonal deviations) to account for the above-mentioned endogeneity and potential unobserved individual effects.

The paper complements other micro-econometric studies that estimate habit formation coefficients. Again, the micro-perspective is important, because — unlike macro data — micro data displays much higher fluctuation and captures heterogeneity at the household level. The paper makes four *contributions* to the existing literature. First of all, the data set has a large cross-sectional dimension, but more importantly, a relatively large time series dimension. Similar studies have only very limited time-series support, which is associated with Nickel-bias. Second, I use total household consumption data and not — unlike most available micro-econometric studies — food consumption as a questionable proxy thereof. It is important to stress that the results on total household consumption

[4] Blundell et al. (2004) suggests a solution to the lack of total household consumption data. In particular, he combines the overlapping data sources of the PSID (Panel Study of Income Dynamics, containing panel data on food consumption) with the CEX (Consumer Expenditure Survey, containing cross-sectional data on multiple classes of consumption). Thereby, total household consumption can be estimated. Nevertheless, conclusions based on synthetic data should be done cautiously.

[5] See Engel's law. There are necessary goods and luxury goods. Food is commonly seen as a necessary good; its relative share declines with increasing income. Furthermore, there are life-cycle-related differences in consumption patterns (hump-shaped life-cycle consumption path).

have a much broader applicability to common economic questions and modeling. The third contribution is the nested analysis of internal and external habits. The feasibility of this endeavor is linked to the availability of total household consumption data. Otherwise, the analysis of external habits would not make sense, because people observe overall spending patterns of others (conspicuous consumption; Veblen (1899)); not necessarily what others eat at home. Put differently, social comparison is more likely for status and luxury goods, and not so much for basic consumption, such as food. The fourth contribution is the investigation of two important, but different measures for external habits. In particular, I differentiate between two special types of external habits: inequality aversion and "keeping up with the Joneses" (KUWJ) preferences. The differences among the two concepts are described later on.[6] To my knowledge, all available studies proxy the external habit with average aggregate consumption or spatial refinements (state-level, city-level, zip-code level). This implies that the estimated coefficient reflects the strength of inequality aversion; not KUWJ.

The baseline results provide evidence for internal and external habit formation in consumption and suggest that the external habit is about three times as large as the internal habit. Hence, social comparison seems more important than internal habituation. One explanation why other studies do not find evidence for internal habits is their use of food consumption data. In fact, when I estimate the internal habit effect with food consumption data only, the coefficient is much lower than in the baseline scenario with total household consumption. Neither the internal habit coefficient, nor the external habit coefficient are sizable enough to explain important empirical regularities in macroeconomics and finance. Deaton (1987) and Constantinides (1990), for instance, show that the habit coefficient should be around 0.8 to explain the excess smoothness of aggregate consumption, or the equity premium puzzle. Even the sum of the estimated internal and external habit effects accounts for less than fifty percent of the theoretically determined number (0.8). This implies that using the baseline coefficients of this study would predict a consumption smoothing behavior that is excessive compared to the predictions of a permanent-income hypothesis model, but below the actually observed smoothness of aggregate consumption. Moreover, the coefficients could only partly explain the equity premium puzzle. The results of an extended model with KUWJ preferences, however, produce coefficient estimates that can be reconciled with the theoretically determined number.

[6] Inequality aversion implies that both the low-expenditure consumers and the high-expenditure consumers compare their consumption to the average consumer. They try to avoid strong deviations from this average. KUWJ means that people look at the consumption of other people who can afford similar consumption patterns, but are slightly ahead (therefore: keeping up). The terms external habit and KUWJ are often used interchangeably, although KUWJ is a special case of external habits.

The remainder is organized as follows. Section 2 derives an econometrically testable Euler equation from a structural model. Section 3 describes the data set. Section 4 discusses estimation issues. In section 5, I present the main results and a robustness check. Finally, section 6 concludes the paper.

3.2 Model

The derivation of the model borrows from Korniotis (2010). It is slightly altered to fit the micro-econometric focus on household consumption data that is used in this paper.

3.2.1 Household Preferences

The periodic utility function, $U_{i,t}$, of household i in time t is given in terms of a difference between consumption and the consumption habits:

$$U_{i,t}(C_{i,t}, I_{i,t}, X_{i,t}) = e^{-\beta_i}(1-\lambda)^{-1}(C_{i,t} - \pi_1 I_{i,t} - \pi_2 X_{i,t})^{1-\lambda} \ . \tag{3.1}$$

C denotes the contemporaneous consumption level, I the internal habit, and X the external habit. The term $e^{-\beta_i}$ represents the time preference, which is assumed individual-specific in line with micro-economic studies (Zeldes (1989), Attanasio and Weber (1995)). The discount rate, β_i, is assumed to be smaller than 1. The term λ denotes the curvature parameter.[7] For notational convenience taste shifters (further explanatory variables) are suppressed. The coefficients π_1 and π_2 reflect the strength of internal and external habits, respectively. To capture the notion of habits (and to be well-behaved), π_1 and π_2 are supposed to lie in the interval [0,1].

In the baseline specification, the internal habit is given by the first time lag of own consumption, $I_{i,t} \equiv C_{i,t-1}$, which follows Ferson and Constantinides (1991). Following Abel (1990), the external habit is given by contemporaneous average aggregate consumption, $X_{i,t} \equiv \bar{C}_{i,t}$. More specifically, I use the average of the state the individual lives in. The reason is that people compare themselves to others that have similar characteristics. Here, this is expressed through higher geographical proximity at the state-level, compared to the country-level. Inserting the expressions for internal and external habits into equation (3.1) yields:

[7] The curvature parameter is related to relative risk aversion (RRA) as follows: $RRA = \frac{\gamma}{S_t}$, where $S_t = \frac{C_{i,t} - p_1 C_{i,t-1} - p_2 \bar{C}_{i,t}}{C_{i,t}}$ (Campbell and Cochrane (1999)).

$$U_{i,t}(C_{i,t}, C_{i,t-1}, \bar{C}_{i,t}) = e^{-\beta_i}(1-\lambda)^{-1}(C_{i,t} - \pi_1 C_{i,t-1} - \pi_2 \bar{C}_{i,t})^{1-\lambda} \ . \tag{3.2}$$

The negative sign in front of the coefficients indicates the direction of the habits on utility. In fact, the theory suggests that both $C_{i,t-1}$ (internal habit) and $\bar{C}_{i,t}$ (external habit) lower current utility.[8] The robustness section of the results considers alternative habit specifications.

3.2.2 Econometric Model

The econometric model is derived from the Euler equation of the households. At first, the Euler equation for a time-varying, risk-free, interest rate, R_t, is obtained.[9] The availability of an asset with interest rate R_t allows people to carry resources from one period to another. Optimal behavior implies that the marginal cost (net utility loss) of a reduction in current consumption equals the marginal benefits (net utility gain) of a consumption increase one period later. Hence, I equate the marginal costs and benefits, which results in the following Euler condition

$$MU_{i,t} - \pi_1 E_t e^{-\beta_i} MU_{i,t+1} = E_t e^{-\beta_i} R_{t+1}(MU_{i,t+1} - \pi_1 E_{t+1} e^{-\beta_i} MU_{i,t+2}) \ , \tag{3.3}$$

in which $MU_{i,t} \equiv (C_{i,t} - \pi_1 C_{i,t-1} - \pi_2 \bar{C}_t)^{-\lambda}$. For estimation purposes, equation (3.3) is simplified hereafter. One reason is that endogeneity requires instrumental variable estimation. The limited number of available instruments are unlikely to capture the nonlinearities adequately, and hence, might produce unconvincing estimates. In this context, endogeneity stems from the lagged dependent variable (LDV) — lagged consumption — which enters the equation. Moreover, endogeneity can arise due to measurement error in consumption. In addition, there are specific problems that arise when estimating consumption Euler equations with micro-data (Dynan (2000)). The established methods provided by the literature emphasize the treatment of linear equations. Following Deaton (1992), I express equation (3.3) as a second-order difference equation in marginal utility. The solution to this difference equation has to satisfy the subsequent relationship:

[8] A negative coefficient of π_1 would be associated with durability. While an internal habit smoothes consumption, durability renders the consumption path lumpy.

[9] The interest rate is time-varying. It is, however, constant across individuals, as the data set provides no individual-specific interest information.

$$MU_{i,t} = E_t e^{-\beta_i} R_{t+1} MU_{i,t+1} \ . \tag{3.4}$$

The equation holds exactly if the interest rate is constant over time (Ravina (2007), Hayashi (1985)). The data section shows that there is hardly any variation in the interest rate, and hence, the equation is approximated well. If agents display rational expectations, the forecasting error of the conditional expectation is uncorrelated with all information available at time t:

$$MU_{i,t} = e^{-\beta_i} R_{t+1} MU_{i,t+1} + e_{i,t+1} \ . \tag{3.5}$$

Hence, the forecasting error is assumed to have mean zero. Following the conventions in the empirical consumption literature, I log-linearize equation (3.5) around the steady state (Korniotis (2010), Dynan (2000), Fuhrer (2000), Vissing-Jorgenson (2002), and Ravina (2007)). Log-linearization yields

$$\Delta c_{i,t} = \pi_0 + \pi_1 \Delta c_{i,t-1} + \pi_2 \Delta \bar{c}_{i,t} + \pi_3 r_t + \varepsilon_{i,t} \ , \tag{3.6}$$

in which Δ denotes the difference operator, $\pi_0 = -\beta_i$, and $\pi_3 = (1 - \pi_1 - \pi_2)/(\gamma)$ represents the elasticity of inter-temporal substitution. Lower-case letters denote the logarithm of a capital letter variable, so that $c = ln(C)$ and $r_t = ln(R_t)$. The composite error consists of higher-order terms that were ignored by the log-linearization, and the prediction error.[10] At this point, I include taste-shifters, T, and their corresponding coefficient matrix Π. Taste shifters (control variables) capture individual differences among people. The linearized model is better suited to account for unobserved individual effects, for instance, individual-specific time preferences. Moreover, it leads to additive terms of the parameters R_t and β_i, which could otherwise not be distinguished with the current data set. Ultimately, this leads to the following dynamic regression model, which is estimated with the data set.

$$\Delta c_{i,t} = \pi_0 + \pi_1 \Delta c_{i,t-1} + \pi_2 \Delta \bar{c}_{i,t} + \pi_3 r_t + T'_{i,t} \Pi + \varepsilon_{i,t} \tag{3.7}$$

[10] In line with the existing literature, I assume that the higher-order terms are either constant or uncorrelated with the instrument set. In table (B.2), I include higher-order terms as robustness check. The lag of squared consumption growth (consumption variance) is highly significant, but does not influence other estimates.

Again, π_1 and π_2 reflect the strength of the internal and external habit, respectively. The error term is assumed to have zero mean. No assumptions are made on the error auto-correlation. Rather, the auto-correlation is tested empirically.

3.3 Data

3.3.1 Describing the Data Set

The RAND American Life Panel (2013) comprises a large representative sample of people living in the United States. People are repeatedly asked to fill out the same survey on a monthly basis. Data is collected from May 2009 to April 2013. This provides panel data for 48 consecutive months. All observations are obtained after the financial crisis, and hence, major policy shifts (structural breaks) are unlikely. Moreover, the fact that all data points are collected within four years, guarantees that the wording and response categories of the questionnaire remain constant. Specifically, people are asked the same questions and are provided with the same set of answer possibilities. This eliminates the time-comparability problem that is found in other surveys. Additionally, the high-frequency data — surveys are answered monthly — mitigates recall and reporting error.

3.3.2 Dependent Variable: Household Consumption Growth

The dependent variable is total household consumption growth. Total household consumption is the sum over the available 25 consumption categories. Formally, $C = \sum_{j=1}^{25} C_j$, where j represents the consumption categories. The consumption categories exclude big ticket items, such as, furniture, ovens, and dish washers. These big ticket items, or durables, are bought very irregularly and infrequently, so that the purchases do not really coincide with the actual consumption. For goods that are bought at a regular monthly frequency, however, an approximate congruence between purchase and consumption is warranted. Hence, a downward bias of the internal habit coefficient due to durability is at least mitigated.

3.3.3 Explanatory Variables of Focus

The explanatory variables of main interest are the internal and external habit formation proxies. The internal habit is proxied by the one-month lag of own consumption, $I_{i,t} \equiv C_{i,t-1}$. For the external habit, I follow Gali (1994), and proxy it by contemporaneous

average consumption.[11] More specifically, I choose the average consumption of the US state, where the individual lives in: $X_{i,t} \equiv \bar{C}_{i,t}$. The bar above the C signals that this is an average value. Proceeding like this is supposed to capture one specific notion of external habits, namely inequality aversion: people with low consumption look upwards (to the average consumer), whereas people with high consumption look downwards. All of them dislike strong deviations from the average value. Alternatively, the social reference value could be given by "keeping up with the Joneses" preferences. These are investigated in section 5.2.

3.3.4 Control Variables

The control variables capture the financial situation, perceived health, and standard socio-economic aspects. Some variables, such as debt, correspond to the sum over all household members. Other characteristics, such as age and employment status, correspond to the head of the household. Available control variables include: interest rate, work income (before taxes and other deductions), credit card debt, stock ownership, home ownership, health coverage, family size, age, age-squared, employment status, marriage status, education, state residency, retirement, and health status. As interest rate, I use the nominal, one-month, constant maturity T-bill, obtained from Board of Governors of the Federal Reserve System (2012). It reflects changes in the inter-temporal price of consumption within the Euler equation. Note that health condition data is not objective medical data, but reflect a person's self-accessed situation. In addition, there are time dummies for each month. They capture aggregate shocks, for instance, price changes. Note that consumption, income, and the interest rate are given in nominal terms. In any case, severe price changes are not expected within the short time span of data collection, especially not on a month-by-month basis. Gender and ethnicity are not controlled for, because time-invariance forbids the estimation of their coefficients after the data is transformed.

3.3.5 Cleaning the Data Set

The following selection criteria (data cleaning) are applied: First, I verify that there are no double-counts in id-variables. Second, the observations where the head of household is below 18 years or above 90 years are excluded. This is, because only a few observations lie outside the 18 to 90 years range, and they might distort the main conclusions. Third, in line with Zeldes (1989), I eliminate questionable consumption observations, in which

[11] Other studies include a past-period lag or a weighted structure of current and past terms. Clearly, my choice provides a simplification over more complex specifications. But, it is unconvincing that real people are influenced by the complete history of individual and aggregate consumption.

consumption grows by more than 300 percent or declines by more than 66 percent per month. Stronger consumption changes are probably due to reporting errors. Keep in mind that irregular, big ticket purchases are excluded and cannot be responsible for strong consumption fluctuations. Entries with negative values for consumption, or consumption categories are dropped. Clearly, negative consumption makes no sense. I also delete observations where the sum of food & beverage at home and dining out is below 100 US dollars. The rationale is that people must eat something and values below 100 US dollars are probably input errors. Finally, I eliminate extreme, non-representative consumption and income values that lie outside the upper 99.9 percentile, mainly to exclude input errors.

3.3.6 Data Overview

Table 3.1 presents summary statistics. The data set covers more than 70,000 observations and more than 3,500 households. It is an unbalanced panel with different time series support per cross-sectional unit (household). At best, there are 48 consecutive time waves per individual (on average about 18 observations per individual). Compared to other studies that investigate consumption Euler equations (see introduction and appendix) the time series dimension of this data set is relatively long. Panel gaps are mainly exogenous and not due to sample-selection bias.[12] The head of household might change over time, but this happens very rarely. This is why gender and ethnicity are not included. Both would not be identified, since there is insufficient variation. The response rates for the variables of interest are very high. Thus, I do not expect significant bias due to item non-response. The survey designers intended a representative sample of US individuals. People were asked to participate in the survey and did not self-select themselves. This mitigates worries about endogenous sample selection. Nevertheless, a small endogenous component remains, since people still accept to be part of the sample, but clearly, this is a concern in any type of survey data and equally applies to every experimental study. The potential attrition bias is less severe for individuals than for firms. If firms leave a panel due to bankruptcy, they basically "die". If people leave the panel, they are likely still alive and simply stop participating. If this non-participation is unrelated to the unobserved component, and not confined to specific sub-populations, this is no problem.

Table 3.2 depicts the auto-correlation in consumption growth, Δc. There is a sizable effect at the zero (negative) and annual (positive) frequency.

[12] Some households started to participate in the survey only in later waves. I lost several observations due to the data cleaning that is outlined above.

Table 3.1: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
HH consumption	3062.875	2088.503	100	33438	74717
HH work income*	2395.131	3757.770	0	63900	74717
HH credit card debt	1.245	0.732	1	6	74717
interest	0.061	0.053	0	0.16	74717
family size**	0.918	1.321	0	10	74716
stock owner	0.313	0.464	0	1	74482
home owner	0.757	0.429	0	1	71696
health coverage	0.891	0.312	0	1	71484
male	0.395	0.489	0	1	74717
age	52.781	14.184	18	90	74717
education	4.131	1.570	1	8	74717
working	0.548	0.498	0	1	74717
married	0.651	0.477	0	1	74717
health condition	3.416	0.905	1	5	73241
state residence	24.945	14.743	1	52	74716
white	0.896	0.305	0	1	74717
black	0.056	0.231	0	1	74717
native	0.005	0.071	0	1	74717
asian	0.017	0.130	0	1	74717
other	0.025	0.156	0	1	74717

This table provides summary statistics for all variables. The abbrevation HH stands for household. Consumption represents total household consumption expenditures across all goods. *Work income is set to zero if people report unemployment, which explains the low mean value. The mean of work income, conditional on being greater than zero, is 4,055 US dollar. **Family size counts the number of people in addition to the head of household. Interest is measured in percent.

Table 3.2: Auto-Correlation in Consumption Growth

	Δc	L. Δc	L2. Δc	L3. Δc	L4. Δc	L5. Δc	L6. Δc	L12. Δc	L24. Δc
Δc	1								
L1.	-0.4282	1							
L2.	-0.0242	-0.4326	1						
L3.	0.0013	-0.0290	-0.4376	1					
L4.	-0.0143	0.0049	-0.0391	-0.4162	1				
L5.	-0.0081	-0.0157	0.0012	-0.0538	-0.4182	1			
L6.	0.0296	-0.0043	-0.0057	0.0054	-0.0564	-0.4156	1		
L12.	0.0746	-0.0281	-0.0132	0.0007	-0.0056	0.0093	0.0052	1	
L24.	0.0307	-0.0054	-0.0077	0.0128	-0.0155	-0.0074	0.0165	0.0493	1

The table depicts the autocorrelation in consumption growth. Sizable auto-correlation is found at the zero and annual frequency. At other frequencies, the auto-correlation is close to zero.

3.4 Estimation Issues

Three issues arise in panel estimations of this type: time aggregation, measurement or recall error, and household-specific fixed effects (unobserved heterogeneity). High-frequency data (monthly) reduces the first two concerns. Moreover, a "smart" survey design, as in Hurd and Rohwedder (2012), mitigates recall and measurement error even further.[13] Their idea is to include a feedback mechanism that instantly reminds respondents of input inconsistencies, and asks them to revise their answers. This data set (ALP) uses the survey design by Hurd and Rohwedder (2012). It is important to disentangle the effect of unobserved heterogeneity and non-separable preferences. Otherwise, the coefficient on the internal habit will be upward-biased. Unobserved heterogeneity can be addressed by first-difference estimation, or the closely related concept of forward orthogonal deviations.

In OLS estimation the identification hinges on the assumption that regressors are orthogonal to the errors. In the case of lagged dependent variables, OLS is often inconsistent, because serially correlated error terms are correlated with the lagged depended variable, which induces endogeneity. The generalized method of moments (GMM) estimator by Hansen (1982) can produce consistent and efficient estimates, but demands for proper instrumentation. Valid instruments must be uncorrelated with the composite error term. But, this is not given if the composite error term contains household-specific fixed effects. Fortunately, I can account for unobserved fixed effects by transforming the data first; and then applying GMM estimation. The GMM estimator is more efficient than IV estimators, as it allows for heteroskedasticity. In particular, the GMM estimator allows for heteroskedasticity and auto-correlation within, but not across individuals. To filter out the error-correlation across individuals, I include time dummies in each regression. They account for time-specific effects, such as price and productivity shocks. This panel data set has large number of households. In comparison, the time dimension is relatively small (T=48 at best). As already mentioned, it is still considerably larger than in similar studies that estimate consumption Euler equations. The large N, small T-nature of this panel, combined with the pre-determined, lagged dependent variable specifically asks for dynamic panel treatment.[14]

[13] They state: "[...] including an important innovation – the *spending reconciliation screen* – designed to catch large outliers that can be more frequent in self-administered surveys, for example, due to typos, and no interviewer to verify unusually large numbers. The reconciliation screen allows respondents to review all of their entries and the resulting total on one screen. Beyond the catching and self-correction of outliers the reconciliation screen also allows respondents to fine tune their entries, most likely reducing the noise in the data and leading to more accurate reports overall" (Hurd and Rohwedder, 2012, p. 3).

[14] Dynamic panel bias typically arises because the LDV is endogenous to the individual fixed effects. If the fixed effects are eliminated, for instance through first-differencing, another issue occurs. The differenced LDV is now correlated with the differenced idiosyncratic error term.

The difference-GMM estimator by Arellano and Bond (1991) differences the data before standard GMM estimation is applied. Arellano and Bover (1995) and Blundell and Bond (2000) suggest an alternative method: the system GMM estimator, which uses the difference and level equation. This maximizes sample size and improves efficiency. While the difference equation is instrumented by levels, the level equation is instrumented by differences. It is important to keep in mind that the method hinges on an additional assumption: the differenced instruments in the level equation are uncorrelated with unobserved fixed effects. Clearly, this is hard to verify.

Since the panel is unbalanced (there are gaps), difference-GMM would eliminate many observations. It is theoretically possible to construct data sets that disappear in differences, as a missing y_t is related to Δy_t and Δy_{t+1}. Therefore, differencing magnifies already existing gaps. A solution that maximizes sample size is the transformation by forward-orthogonal deviations (FOD). For each variable, it computes the average of all future *available* observations and subtracts them from the current value. This is always feasible, even if observations are missing. In fact, difference-GMM and FOD-GMM coincide for balanced panels. For the reasons just mentioned, I use the transformed-GMM estimator with forward-orthogonal deviations.

Roodman (2006) suggests two test-statistics to check for correct model specification in dynamic GMM estimation: the Hansen over-identification J-test and the Arellano-Bond second-order auto-correlation test. The Hansen J-test checks the crucial assumption of instrument exogeneity.[15] The null hypothesis is that instruments are exogenous. A rejection of the over-identification test suggests that the instruments are invalid. The Arellano-Bond second-order auto-correlation test in errors [AB(2)] is based on the GMM assumption that there is no error auto-correlation in the original, non-transformed equation. But even if errors are uncorrelated in the original equation, transformation (differencing) induces serial correlation ($\Delta u_t = u_t - u_{t-1}$). Nevertheless, there should be no sign of second-order correlation in the transformed errors if the assumption of zero auto-correlation in the original equation is maintained. The AB(2)-test, thus, has the null hypothesis that there is no second-order auto-correlation in transformed errors.

There are two ways to instrument the LDV: Either by deeper lags of the LDV, or by excluded instruments. The dynamic GMM routine was developed for the case in which no additional excluded variables are available and the researcher has to use deeper lags of the LDV. The routine, however, allows for excluded instruments, if available. In this paper, no excluded instruments are available. Therefore, I use lags of the LDV. The first lag of the pre-determined LDV is the first candidate for an instrument. When running the

[15] The J-test statistic is asymptotically χ^2-distributed with degrees of freedom equal to number of equations minus the number of parameters.

regression, the AB(2)-test is rejected, though. This suggests that there is second-order correlation, and hence, even deeper lags are needed as instruments. When using the second lag of the LDV as instrument, the AB(3)-test is not rejected. This suggests that the second lag and potentially even deeper lags are valid instruments. Further discussions are provided in the next section.

The Wald-test of joint significance of all covariates is applied as an additional check on correct model specification.

3.5 Results

3.5.1 Main Results

Table 3.3 presents the main results. Time dummies (not reported) are included and jointly significant, meaning that aggregate shocks are present. Column 1 corresponds to equation (3.7), but without any taste shifters. Remember that the coefficient on lagged consumption growth, $\Delta c_{i,t-1}$, is supposed to capture the internal habit effect. The value should lie between zero and one, to reflect internal habit formation. Indeed, the coefficient is about 0.09 and significant at the 1 percent level, suggesting internal habit formation at the monthly frequency. The coefficient on state-level consumption growth, about 0.27, lies in the credible range to account for external habit formation (inequality aversion) and is also highly significant. It is three times larger than the internal habit effect. The net rate of interest is insignificant. This might be due to the fact that information is only available at the aggregate level; there is no household-specific interest rate. Furthermore, I cannot differentiate between a lending and borrowing rate. Lastly, the interest is close to the zero lower bound. Hence, there is hardly any variation. The test statistics provide no evidence against correct model specification. According to the Wald-test, the regressors are jointly significant. I cannot reject the null of instrument exogeneity (Hansen's over-identification test), and there is no evidence against the null of no third-order auto-correlation in errors [AB(3)]. Thus, it is valid to instrument the LDV — lagged consumption growth — with its second lag and deeper lags. Column 2 includes the full set of control variables. The coefficients of main interest remain unaffected. Only age squared, working, and credit card debt are highly significant covariates. Age (although insignificant) and age squared hint at a hump-shaped relation between consumption growth and age. This is in line with Carroll and Summers (1991). The non-significance of age is probably caused by the high frequency of the data. There is only little variation, because age in years changes very slowly with monthly data. Education is significant at the 10 percent level and has a negative effect on consumption growth, which is

counter-intuitive. Column 3 uses the same control variables, but uses also the third lag of the LDV as instrument. This does not affect the main coefficients and slightly increases the test statistics (Wald-test, Hansen-test, AB(3)-test). The test statistics give no reason to question model specification. The results in column 3 serve as the baseline in the remainder.

Table 3.3: Strength of Internal and External Consumption Habits - Baseline Results

	(1)	(2)	(3)
Dependent Var: $\Delta c(t)$	basic model	additional controls	additional instrument
$\Delta c(t-1)$; internal	0.0904***	0.0898***	0.0925***
	(0.0195)	(0.0199)	(0.0163)
$\Delta \bar{c}(t)$; external	0.2729***	0.2727***	0.2680***
	(0.0197)	(0.0199)	(0.0202)
interest rate	-0.2081	-0.1996	-0.1721
	(0.1356)	(0.1378)	(0.1379)
household size		-0.0007	-0.0007
		(0.0020)	(0.0020)
working		0.0151***	0.0149***
		(0.0048)	(0.0048)
credit card debt		0.0073***	0.0067***
		(0.0022)	(0.0022)
stock holder		0.0030	0.0031
		(0.0051)	(0.0050)
age		0.0045	0.0050
		(0.0042)	(0.0043)
age^2/100		-0.0074***	-0.0072***
		(0.0027)	(0.0027)
education		-0.0134*	-0.0123*
		(0.0071)	(0.0073)
state residence		-0.0006	-0.0007
		(0.0006)	(0.0005)
home owner		0.0003	0.0018
		(0.0071)	(0.0072)
married		0.0121	0.0117
		(0.0074)	(0.0074)
health coverage		0.0054	0.0071
		(0.0063)	(0.0064)

health condition		-0.0001	-0.0000
		(0.0031)	(0.0031)
Time dummies	Yes	Yes	Yes
Number of observations	49502	46973	46973
Number of households	2620	2607	2607
Wald-test	724.51	740.40	727.95
P-value Wald-test	0.000	0.000	0.000
P-value Hansen-test	0.268	0.186	0.208
P-value AB(3)-test	0.928	0.696	0.740

FOD-GMM (forward orthogonal deviation), two-step, Windmeijer-corrected standard errors.

Instruments - columns 1 and 2: 2nd lag of $\Delta c(t-1)$; column 3: 2nd and 3rd lag of $\Delta c(t-1)$.

95 Percent Confidence Interval for column 2: [0.0508 - 0.1289].

95 Percent Confidence Interval for column 3: [0.0606 - 0.1244].

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

3.5.2 Robustness Checks

In the subsequent tables, I use the same control variables as in the table with the main results. To shorten the tables, the controls are not reported. Tables B.1, B.2, and B.3 provide robustness checks. First, there is no major difference if I run sub-sample regressions on male or female head of households (table B.1). Second, table B.2 includes the higher-order terms that were ignored by the log-linearization. The inclusion of the variance of lagged individual consumption growth and state-level consumption growth has no material impact on the coefficients of main interest. Finally, I test whether including income growth and squared income growth affects the habit coefficients. Income growth significantly contributes to higher consumption growth, albeit with a diminishing effect — squared income growth is negative and significant at the 5 percent level. Once again, the internal and external habit coefficients are robust to the variation of controls.

3.5.3 Comparison with Other Micro-Econometric Studies

Table 3.4 compares the estimated internal habit coefficient of this paper with previous research findings.[16] Admittedly, the estimates are not perfectly comparable, because of different data sets and different time frequencies. Nevertheless, it is interesting to put the findings into perspective. Column 1 provides the reference to the respective research

[16] I do not compare the external habit coefficient, since most other papers provide only the internal habit coefficient.

paper. Column 2 indicates the estimated internal habit coefficient and the significance. Column 3 shows which consumption good was used for the estimations. In most cases, the authors used only food consumption. Column 4 states which estimation method was used and column 5 indicates whether both habit types or only internal habit formation was tested.

Table 3.4: Estimate of the Internal Habit Coefficient

(1) **Source**	(2) **Coefficient**	(3) **Consumption**	(4) **Estimation**	(5) **Habits**
This paper	0.0925***	total	FOD-GMM	both
	0.0912***	total	FOD-GMM	internal
	0.0181	food	FOD-GMM	internal
Dynan (2000) Table 2	-0.038*	food	GMM	internal
Guariglia and Rossi (2002)	-0.262***	food	GMM	internal
Table 2	-0.272***	food	S-GMM	
Iwamoto (2011) Table 3	-0.305***	food	S-GMM	internal
Ravina (2007) Table 6	0.503***	credit card	GMM	both

The table compares my coefficient estimates (rows 1 to 3) to other papers. Row three presents estimates when only food consumption is considered — and not total consumption. This helps to determine where the differences in the estimated coefficients come from. The subsequent rows indicate the main results of other authors. Stars denote the significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimate in the first row shows the baseline result of this paper. The second row provides the coefficient on internal habit formation, when the external habit is dropped from the regression equation. Apparently, the internal habit coefficient is unaffected. In the third row, I provide an estimate of internal habit formation, when only food consumption is used. In this case, the internal habit coefficient becomes insignificant and is close to zero.

All papers that use food consumption find a negative sign on lagged consumption growth, and thus, reject internal habits in favor of durability: Dynan (2000) finds a significant and slightly negative (-0.038) coefficient. Guariglia and Rossi (2002) and Iwamoto (2011) find significant and sizable negative coefficients (ranging from -0.305 to -0.262).

Ravina (2007) uses credit card data, which is a broader consumption measure than food consumption. Contrary to the other studies, she finds very strong support for internal habit formation (0.503). One explanation is that she has information on the household-specific interest rate. After dropping the household-specific interest information, her coefficient drops, but remains significant and positive (0.13). In fact, her estimates are very close to this paper's estimates, when total consumption is used. Using food, instead of total consumption, at least partly explains the gap between the positive coefficients of Ravina (2007) and the negative coefficients of Dynan (2000), Guariglia and Rossi (2002), and Iwamoto (2011). The coefficient of lagged consumption growth — the supposed internal habit measure — is simply higher for total consumption than for food consumption. Nonetheless, it remains questionable where the strong negative values of some studies stem from.

3.5.4 Extensions

3.5.4.1 External Habit: Keeping Up with the Joneses

So far, I used state level consumption as proxy for the external habit. Remember, that this is supposed to reflect inequality aversion. As alternative, I introduce a proxy for keeping up with the Joneses (KUWJ) preferences. The idea is that people compare themselves to other people, who are at a similar point on the consumption distribution. In other words, people compare themselves to others who consume equal amounts. I divide the households into groups, according to their consumption expenditures. In particular, consumption group 1 includes all households with monthly consumption up to 1,000 US dollars. The other consumption groups are defined by 1,000 US dollar increments. Hence, consumption group 10 includes households where consumption ranges from 9,000 to 10,000 US dollars. The final consumption group (11) includes all households that spend more than 10,000 US dollar per month. I use two slightly different measures to proxy KUWJ preferences. This is supposed to avoid any speculation that the findings hold only for one particular measure. Measure A takes the central consumption value within each consumption group. This implies that people compare themselves to the "average person" within their own consumption group. Measure B, however, uses the upper ceiling of the respective consumption group. Thus, people compare themselves to the "best person" within their own peer-group. Details are given in table (3.5).

Table 3.6 shows the results for the Joneses preferences. For comparison, column 1 presents the baseline results. Column 2 uses measure A to account for Joneses preferences. Column 3 uses measure B. The KUWJ coefficient is very sizable and significant at the 1 percent level. It is slightly lower for measure A (0.6993 in column 2) than for measure

Table 3.5: Two Measures for "Keeping Up with the Joneses" Preferences

Group	**Monthly Consumption**	**Comparison Consumption**	
		Joneses A	**Joneses B**
1	0-1000	500	1000
2	1000-2000	1500	2000
3	2000-3000	2500	3000
4	3000-4000	3500	4000
5	4000-5000	4500	5000
6	5000-6000	5500	6000
7	6000-7000	6500	7000
8	7000-8000	7500	8000
9	8000-9000	8500	9000
10	9000-10000	9500	10000
11	above 10000	15000	15000

The table presents two alternative measures for "Keeping up with the Joneses" preferences.

B (0.7889 in column 3). The inclusion of the Joneses measures reduces the impact of the internal habit to one third of its original size (from 0.09 to 0.03). In column 4, state-level consumption growth (inequality aversion) and the Joneses measure B are jointly included. The Joneses measure remains unaffected. The state-level consumption growth coefficient more than doubles compared to the baseline in column 1. Evaluating the Arellano-Bond test statistics in column 4, however, rejects the null hypothesis of no third-order auto-correlation in errors. Therefore, the results from column 4 should be considered suspiciously. The test statistics for columns 1 to 3, however, provide no sign of model misspecification.

In general, accounting for the Joneses preferences lowers the internal habit coefficient, compared to the baseline. Nevertheless, the internal habit coefficient remains highly significant. Apparently, external habit coefficients of both types — inequality aversion and KUWJ — have a strong effect on individual consumption decisions. Among the two external habits, KUWJ seems much stronger than inequality aversion (state-level consumption growth).

Table 3.6: Keeping Up with the Joneses Preferences - Extended Results

	(1)	(2)	(3)	(4)
Dependent Var: $\Delta c(t)$	baseline	Joneses A	Joneses B	simultaneous
$\Delta c(t-1)$; internal	0.0925***	0.0332***	0.0326***	0.0370***
	(0.0163)	(0.0077)	(0.0078)	(0.0082)

$\Delta\bar{c}(t)$; external	0.2680***			0.5670**
	(0.0202)			(0.2477)
keep up with Joneses A		0.6993***		
		(0.0067)		
keep up with Joneses B			0.7889***	0.7747***
			(0.0087)	(0.0102)
Control variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Number of observations	46973	46973	46973	46973
Number of households	2607	2607	2607	2607
Wald-test	727.95	12959.64	10070.62	10744.81
P-value Wald-test	0.000	0.000	0.000	0.000
P-value Hansen-test	0.208	0.571	0.479	0.752
P-value AB(3)-test	0.740	0.081	0.085	0.030

FOD-GMM (forward orthogonal deviation), two-step, Windmeijer-corrected standard errors.

Instruments: 2nd and 3rd lag of $\Delta c(t-1)$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.4.2 Internal Habit: Long-Term Effect

Heaton (1995) suggests that the internal habit does not necessarily materialize in the short-term, but might build up over time. To investigate this hypothesis, I augment the model by a long-term internal habit effect. In particular, I add the 12-month (1 year) lag and 24-month (2 years) lag of consumption growth to the model. This looks as follows

$$\Delta c_{i,t} = \pi_0 + \pi_1 \Delta c_{i,t-1} + \pi_2 \Delta c_{i,t-m} + \pi_3 \Delta \bar{c}_{i,t} + \pi_4 r_t + T_{i,t}^{'} \Pi + \varepsilon_{i,t} \ , \tag{3.8}$$

with m being either 12 or 24. I choose these two specific lag length, because they have the highest auto-correlation with current consumption growth, in table 3.2. The estimates are presented in table 3.7. Column 1 presents the baseline result for comparison. Column 2 and 3 add the 12-month and 24-month long-term habit, respectively. In column 4 they are included jointly. Both long-term habits are highly significant, but small in size (ranging from 0.0309 to 0.0552). The positive coefficient on long-term internal habit formation is consistent with Heaton (1995). The short-term internal habit declines if the long-term internal habits are included. If both long-term habits are included jointly, the short-term effect becomes even insignificant. The external habit (inequality

aversion) remains basically unaffected. The test-statistics give no indication of model misspecification. The size of the internal habit coefficients is too small to account for the empirical regularities that habit formation is supposed to be responsible for — even if the coefficients would be summed up.

Table 3.7: Long-Term Internal Habit Effect - Extended Results

	(1)	(2)	(3)	(4)
Dependent Var: $\Delta c(t)$	baseline	long-term 1 year	long-term 2 years	all
$\Delta c(t-1)$; internal	0.0925***	0.0704***	0.0651**	0.0449
	(0.0163)	(0.0201)	(0.0294)	(0.0301)
$\Delta c(t-12)$; internal		0.0431***		0.0552***
		(0.0092)		(0.0118)
$\Delta c(t-24)$; internal			0.0366***	0.0309***
			(0.0107)	(0.0111)
$\Delta \bar{c}(t)$; external	0.2680***	0.2338***	0.2304***	0.2042***
	(0.0202)	(0.0223)	(0.0275)	(0.0272)
Control variables	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Number of observations	46973	26366	16196	13916
Number of households	2607	1603	1357	1224
Wald-test	727.95	510.68	307.41	341.59
P-value Wald-test	0.000	0.000	0.000	0.000
P-value Hansen-test	0.208	0.303	0.166	0.290
P-value AB(3)-test	0.740	0.746	0.651	0.863

FOD-GMM (forward orthogonal deviation), two-step, Windmeijer-corrected standard errors.

Instruments: 2nd and 3rd lag of $\Delta c(t-1)$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusion

This paper tests the first-order condition from a preference specification with internal and external habits. Similar research mostly relies on food consumption data to investigate habit formation. The literature, though, provides evidence that food consumption constitutes a bad proxy for total household consumption. First, Shea (1994) shows that food consumption preferences differ considerably from consumption preferences of other goods. Second, Attanasio and Weber (1995) strongly reject separability between food

and other consumption preferences. (Dynan, 2000, p. 401) states that "the key question — whether the strength of habits in food is the same as that for the average consumption good — has no obvious answer".

This data set allows me to investigate habit formation preferences with total household consumption data, and hence, to answer Dynan's question. The estimates support internal habit formation in adjacent month. This is in contrast to other renowned papers (except for Ravina (2007)), who reject habit formation and instead find negative coefficients on lagged consumption growth (see table 3.4). I show that part of the differences stem from the fact that they use only food consumption, whereas I use total consumption. In fact, if I use only food consumption data, my internal habit coefficient drops as well — albeit not as strong as suggested by the other authors. There is a significant, albeit small long-term effect of internal habits. External habits are highly significant and of important economic size. In particular, the coefficient on KUWJ preferences is much stronger than inequality aversion. In summary, individual consumption decisions are influenced much stronger by social comparison than internal habituation.

Habit formation is supposed to solve empirical regularities that cannot be reconciled with the permanent-income hypothesis life-cycle model (Modigliani and Brumberg (1954) and Friedman (1957)). Deaton (1987) and Constantinides (1990) show that the habit coefficient should be around 0.8 to explain the excess smoothness of aggregate consumption and the equity premium puzzle. Carroll and Weil (1994) suggest an even higher value (0.95) to explain that high aggregate income growth is followed by high aggregate savings. Obviously, the estimates on internal habit formation (about 0.1 in the baseline estimation) cannot account for these values. The sum of internal and external — inequality aversion (about 0.27) — coefficients amounts to 0.37 and is less than half the value that is needed to explain the aforementioned empirical regularities with habit formation models. The estimates on the KUWJ preferences, however, lie in a credible range (0.6993 - 0.7889). Consequently, external habits (KUWJ) can account for the above-mentioned empirical patterns.

The findings are relevant to three strands of the literature. First, they provide microeconometric evidence to the theoretical research body that assumes the presence of habits. They also indicate that one should focus on inter-dependent preferences, rather than only on time non-separable ones. Second, the coefficients can inform welfare analysis that is based on an extended utility function with adaptation and social reference points. Third, it is of interest to heterogeneous agent models and simulations, where social comparison among different agents plays a vital role.

Note that the results are pegged to the assumption of *perfect rationality*. This paper, as well as the aforementioned studies, estimate equations that arise from an

optimization problem. Put differently, they investigate "rational" habit formation. Rather, as suggested by Muellbauer (1988), a person's consumption choices might be better described by "myopic" habits. This means that people "feel" the habit effect, in the sense that past consumption levels lower their current utility. But on the other hand, they do not understand (or incorporate) that their current consumption choice will affect their future utility. In fact, it is reasonable that real-life decision makers — that is, boundedly rational people — do not fully anticipate the inter-temporal character of the habit-formation process. The investigation of "myopic" habits is an interesting agenda for further research. Furthermore, the complex interplay between different social references points (Joneses, inequality aversion) deserves further investigation.

Chapter 4

Life-Cycle Consumption, Asset Allocation, and Pension Design under Non-Standard Preferences

4.1 Introduction

This paper combines non-standard decision preferences with income heterogeneity to investigate pension design in Germany. In particular, it tries to answer two questions. First, does Germany's current non-funded social security system benefit from a transition towards a fully-funded pension scheme? Second, is the desirability of a particular pension scheme dependent on a person's income class? In other words, do the rich and the poor ask for different pension design?

The investigation of pension systems deserves special attention, because pension systems are facing enormous sustainability problems nowadays. The sustainability problems are mainly due to rapid demographic change; particularly, declining birth rates and increasing longevity; and low productivity growth.[1] Rising income inequality combined with pension contribution ceilings for the upper income class amplify these problems. Finally, the sustainability issues are magnified by the recent financial crisis and the European debt crisis.

The existing literature typically evaluates pension systems through the lens of the standard economic model — based on the rational choice paradigm and the representative agent framework (Abel (2001), Campbell et al. (2001), Diamond and Geanakoplos (2003)). In reality, however, income heterogeneity and cognitive limitations are an

[1] This puts a higher pressure on the working-age generation of the economy, reflected by an increasing old-age dependency ratio. The old-age dependency ratio (OADR) is commonly defined as follows: people who receive pensions divided by the people who provide the necessary means; OADR = (number of people aged 65 and above)/(number of people aged 15-64) x 100.

important concern. In particular, the behavioral literature identifies five major deviations from the homo oeconomicus. First, people are boundedly rational. They do not maximize, but use simplified decision rules instead (Gabaix and Laibson (2000), Gabaix and Laibson (2005), Pemberton (1993)) — especially, when decision-making involves very complex tasks (Ford et al. (1989), Payne et al. (1993)). Second, people react to reference values. This has two dimensions: reference values in their own past (internal habits) and social reference values (external habits).[2] Third, people are loss-averse, meaning that current consumption is evaluated as a gain or loss compared to past consumption. Prospect theory states that losses weigh much stronger than gains of the same magnitude (Kahneman and Tversky (1979), Bowmann et al. (1999)), which is why people devote more effort towards downward risk protection than towards upward chance seeking. Using the variance, or standard deviation, as a measure of risk aversion does not capture this asymmetry. Fourth, humans are subject to bounded self-control (Laibson (1997), Krusell and Smith (2003)), resulting in an immediate gratification bias. Finally, people are subject to framing effects (Shefrin and Thaler (1988)). Taken together, this asks for a departure from the standard model. In this paper, I focus on the first three deviations.[3]

It is insufficient to evaluate the public pension benefits without considering the private savings that are available upon entering retirement age. After all, people derive value from the sum of the available resources (money), not only from the money that comes in the form of a public pension. Since the private life-cycle savings matter for the pension evaluation, economic models should predict them properly. The amount of savings that are accumulated over working life crucially depend on how a person invests into risky and non-risky assets. Put differently, return spreads between risky assets and risk-free assets make a tremendous difference to life-time wealth. Unfortunately, mainstream economic models do a poor job in describing the life-cycle consumption and asset allocation patterns.

There is, for instance, evidence that neither the traditional permanent-income hypothesis life-cycle model (PIC-LCM), nor the more recent buffer-stock model (BSM), can explain dynamic consumption and investment choices sufficiently.[4] The PIH-LCM (Friedman (1957)) suggests consumption smoothing and cannot explain the excess smoothness

[2] See Campbell and Cochrane (1999), Constantinides (1990), Gomes and Michaelides (2005), Detemple and Zapatero (1992), Wachter (2005), Munk (2008), Abel (1990), Ravina (2007), Korniotis (2010), and Grishchenko (2010).

[3] There is one important issue. Most scholars agree that the standard model faces substantial limitations. But, there are a myriad of possible deviations from the status-quo. Thus, it is fairly easy to discard any major deviation as arbitrary, which explains the supremacy of the standard approach. To avoid this, I take the justification of the model assumptions very seriously. All of the proposed deviations have solid empirical support.

[4] The academic literature on dynamic investment and consumption dates back to Merton (1969) and Samuelson (1969)

of consumption. BSMs provide more accurate consumption-saving predictions (Hurst et al. (2010), Carroll (1997), Carroll and Samwick (1997), Gruber and Yelowitz (1999), Hubbard et al. (1995), Tullio et al. (2008)).[5] Sadly, they are less successful in explaining the decomposition of savings into risky and non-risky assets. Guiso et al. (2002) finds that a large proportion of low income individuals — across different countries — do not hold any risky assets in form of stocks. BSMs cannot explain this stock-market participation puzzle. Furthermore, they cannot explain that saving rates and equity shares increase with income, for a given period. BSMs suggest that equity shares are highest for the young and declining with age (Cocco et al. (2005)), which is in sharp contrast with the data. In particular, Ameriks and Zeldes (2004) show that equity shares are typically very low, or even zero, during young working age, but subsequently increasing with age. Put differently, the young workers typically avoid stocks and start risky investment only at later stages of adulthood. Finally, empirical equity shares are usually much lower than predicted by BSMs.

The main reason why people perform different investment strategies is their risk-attitude. The risk attitude has intrinsic elements, but also depends on the available income. People with higher income are, on average, less risk-averse. Therefore, they typically invest higher shares of total savings into risky assets compared to people with lower income. This is one reason why the paper emphasizes income heterogeneity. For a rigorous pension analysis it is important that the working-age investment patterns of heterogeneous agents are pictured adequately.

Therefore, I employ a model by Binswanger (2011), as it predicts all of the aforementioned asset allocation patters — at least qualitatively — in line with the empirical evidence. The model builds on non-standard decision-rules that are a priori very realistic and easily justified. Essentially, the model agents follow three hierarchically ordered goals. They cannot trade a lower-ranked goal against a higher-ranked goal. This is modeled by lexicographic preferences: once a higher-ranked preference is satisfied, the next, lower-ranked preference is triggered. The ranking of the goals is intuitive and in accordance with the pyramid of needs by Maslow (1943) — derived from well-established psychological underpinnings. Put simply, people want to insure minimum consumption levels first, care about social comparison in consumption second, and finally, want to accumulate as much money as possible. The novelty of the model is that the boundedly rational agents can make prudent and forward-looking choices without the requirement of a full contingent plan. This means they do not pre-specify all future consumption

[5] Buffer-stock models assume that people have a specific *wealth-to-permanent-income ratio* target in mind. If the ratio exceeds the target, consumption increases. Otherwise, savings increase and serve as a buffer for bad times. The model predicts that average consumption growth follows average income growth (Attanasio et al. (1999), Laibson et al. (1998), Gourinchas and Parker (2002), Cagetti (2003)).

choices, but only the minimum consumption levels for the future (see preference section). This reduces the cognitive load of decision-making dramatically.[6] Analytical tractability is preserved.

The preferences bear a certain resemblance with models of internal and external habit formation (Ravina (2007), Korniotis (2010), Grishchenko (2010)), by considering own consumption in other periods and the consumption of other people. All of these habit formation models are generalizations of the expected utility and expected discounting model. The difference in the current model is that internal and external motives are not followed simultaneously. Rather, the external goal becomes only relevant after the internal goal is achieved.

The paper makes three contributions. First, it employs a behavioral model that is capable to address empirical regularities that are especially relevant for the question of pension design. Second, I make several changes to the model by Binswanger (2011); adapting it to the current research question. The original model preferences build on a log specification, which fixes the value of the curvature parameter to one. I allow more flexibility by considering a functional form that resembles HARA preferences, allowing a parametrization of the curvature parameter that fits the data well. Also, I treat minimum stock returns differently than Binswanger (2011). While he picks a value from the lower one percent percentile of a random stock return simulation, I set the minimum stock return simply to zero. After all, this implies the loss of the entire portfolio (bankruptcy of the firm), which corresponds better to the downward risk protection and loss aversion preferences of human beings. Very importantly, I model specific pension formulas (fully-funded (FF) versus Pay-As-You-Go (PAYG)) that account for wage dispersion among individuals. Unlike representative agent models, this renders the PAYG pension benefits dependent on the individual labor income path — not only on the aggregate wage development. This provides the foundation for the investigation of whether different income classes demand, or benefit from, different pension schemes. In addition, the model is carefully parametrized for the German case. A third contribution is that the positive model is not an end in itself, but is fruitfully applied to the normative evaluation of different pension schemes. Research cannot clearly inform us how, and at which point, people trade downward risk protection against maximization of expected values. As a consequence, I evaluate individual well-being according to two metrics: *average life-time value* and *minimal life-time value*. Only if the overlap of both metrics favors one pension

[6] Standard expected utility maximization entails the pre-specification of future consumption choices for all possible states of the world. That is, people are assumed to derive optimal consumption plans by solving the model by backwards induction. Clearly, this can be an extremely challenging cognitive task, because life-cycle decisions cover multiple periods and tremendous uncertainty. The actual computation would require a super-computer.

scheme over the other, a definite pension recommendation is made.

I find that all income classes can benefit from the introduction of a fully-funded pension scheme. Policy-makers have been reluctant to move towards funded pension schemes. On important argument is that low-income individuals might not have the appropriate means to be self-sufficient and need the governmental redistribution schemes. The analysis, however, suggests that a fully-funded pension scheme with an asset that provides low, but risk-free returns can provide better downward risk-protection than a Pay-As-You-Go scheme — given reasonable projections on demographic and financial developments. Sensitivity checks are performed.

The remainder is organized as follows. Section 2 presents the stylized three-period model. In section 3, I assign baseline parameters in line with the literature and own computations. Section 4 presents the simulation results. The model's predictions are compared to the empirical regularities. Afterward, the favorability of the different pension schemes is analyzed. The results are discussed in detail and a robustness check is conducted. Section 5 concludes.

4.2 Model

I consider a three-period consumption-saving life-cycle model, with three overlapping generations per period: the young working generation, the middle-aged working generation, and the old retired generation. Children are ignored as they do not participate in the labor market, and neither contribute nor receive resources from the pension system. The three-period model is chosen for three reasons. First, the model divides the working generation into young and middle-aged people, as it seeks to capture the empirical feature that young and middle-aged individuals display very different consumption and investment patterns. This happens because young people face a much longer expected life span than middle-aged people. Consequently, they are subject to more uncertainty and behave more risk-averse. It is an important feature of this model that a middle-aged person is not simply a financially scaled-up version of its younger self, but that the decision-making mechanism differs. Second, a two-period model — in which only a working generation and a retirement generation exists — would lead to trivial second period decisions, where people simply consume everything and save nothing (assuming that there is no bequest motive). In this model, this trivial decision-making is left for the third period, which allows divergent behavioral patterns in the first and second period. Third, partitioning adult life into three stages corresponds well to the actual life-cycle of human beings, and allows a simple and straightforward parametrization. In particular, I assume the following simplified life-cycle path. Young workers are aged 25 to 44. Middle-aged workers are

aged 45 to 64. Old people retire with 65 years, and live until the age of 84. Clearly, each period has the same length — 20 years.

Two limitations apply. First, the model assumes that there exists a risk-free asset with non-negative net return. Second, it is only a partial equilibrium model, which does not allow for a general equilibrium feedback mechanism. In particular, aggregate wages are invariant to the choice of the pension system and wages are not modeled in relation to the aggregate capital stock and the overall asset returns.

4.2.1 Demography

People earn wages when young (y) and middle-aged (m). Upon entering retirement age, the old people (o) stop working and receive pension benefits. Old people are dubbed retirees. A person's age (young, middle-aged, or old) is indicated by a super-index, while the sub-index represents the time period. Each person lives for a fixed amount of time. For simplicity, I assume that people live until the last day of the old-age period and do not die beforehand. This ensures that the population size, N, of a particular cohort remains constant over time.

$$N_t^o = N_{t-1}^m = N_{t-2}^y \tag{4.1}$$

Incoming cohorts are larger than previous ones, which leads to population growth. The population growth rate, n, is constant.

$$N_t^y = N_{t-1}^y(1+n) \tag{4.2}$$

In each period, t, the labor force, L_t, consists of the number of young and middle-aged workers: $L_t = N_t^y + N_t^m$. For simplicity, I do not model unemployment. The labor force also grows with rate n, such that $L_{t+1} = L_t(1+n)$

4.2.2 Preferences

For complex decisions under uncertainty, people lack the cognitive ability to engage in optimization, as proposed in standard economic theory. This means they are not perfectly rational at all times. More likely, choices are boundedly, or procedural rational, meaning that a decision "is the outcome of appropriate deliberation" (Simon (1976), Simon (1978)). More specifically, decision-making follows simple rule of thumbs, or so-called

heuristics (Payne et al. (1993)).[7] Procedural rational decisions are *reasonable* given that decision-makers are subject to cognitive limitations. In this paper, the preferences are modeled as lexicographic (non-compensatory). This means, people pursue goals that are ordered by importance. Only if a goal with higher priority is satisfied, people start to pursue the next, lower-ranked goal, and so on.

Intuitive Presentation of Preferences In this model, a person's preferences are given by three hierarchically ordered goals: an *insurance goal* (IG), a *reference goal* (RG), and an *accumulation goal* (AG). The *IG* captures four main features of human behavior. People are self-centered, forward-looking, loss-averse, and rapidly adapting. Self-centered means they care about themselves in the first place. Forward-looking means that they are not just living in the moment, but capable and willing to plan for the future. Loss-averse means that losses weigh much stronger (negatively) than gains of the same magnitude. Adaptation means that people are habit forming and get accustomed to a particular life-style relatively fast. Taking these features together, people evaluate their current and potential future life style, and seek to avoid falling arbitrarily below their current standard of living, in the future. Otherwise, they would strongly suffer, because of the relative loss, compared to the earlier condition. In terms of consumption, this implies that people want to ensure a specific fraction of today's consumption for the future, as well. I will refer to this value as consumption habit. The *RG* captures the fact that people not always, or not exclusively, care about themselves. Sometimes, they evaluate themselves in comparison to other people. In terms of consumption, this implies that people not only look at their own consumption, but also how their consumption compares to other people's consumption. I will refer to this as social reference value, or reference consumption. The *AG* captures non-satiation, or humans' never-ending desire for more. If they have enough resources to satisfy their insurance needs, and also can afford to consume above reference consumption, they still want more. In terms of consumption, this means they want to consume as much as possible, or maximize their pecuniary resources.

The ordering of the goals demands some justification. I rely on the findings by Maslow (1943). He explains that consumer needs have the following hierarchy: 1) basic physiological needs (subsistence), 2) insurance and security needs, 3) social needs, and 4) higher individual needs. Basic physiological needs, or subsistence levels, are ensured by the welfare state. The IG, RG, and AG, correspond to the second, third, and fourth need of Maslow's need pyramid, respectively. In other words, a person cares about itself

[7] "Procedural rationality concerns the choice or development of procedures for taking decisions when the decision-maker has effectively limited capacities to process information and calculate appropriate outcomes. Certainly, procedural rationality entails satisficing." ((Moss and Sent, 1999, p. 119))

and insurance first, then about its relative position in society, and finally about the maximization of resources. Once again, note that the idea of the consumption habit is similar to other papers that deal with internal habit formation. Also, the social reference consumption is treated in other papers, commonly referred to as external habit or "keeping up with the Joneses" (Campbell and Cochrane (1999), Pollak (1970), Abel (1990), Gali (1994)). The difference here is that people do not pursue both goals simultaneously, but internal habits first, and external habits second.

Formal Presentation of Preferences Hereafter, I translate the above-mentioned behavioral patterns into mathematical expressions. Under the IG, people maximize a value function that is concave in current consumption, subject to ensuring a minimum of future consumption. Future minimum consumption is supposed to be at least as large as a certain share of current consumption, δ. The consumption share is assumed to be $0 \leq \delta < 1$. Then, the IG in the first period entails:

$$\underbrace{\max}_{c_1, b_1} V_1^{IG} = \frac{(c_1)^{1-\gamma}}{1-\gamma} \; s.t. \tag{4.3}$$

$$c_{2|1}^{min} \geq \delta c_1 \tag{4.4}$$

$$c_{3|1}^{min} \geq \delta^2 c_1 \; . \tag{4.5}$$

The terms $c_{2|1}^{min}$ and $c_{3|1}^{min}$ denote the minimum consumption for period 2 and 3, conditional on period 1 information. The present value of first period *habit consumption*, C_1, is given by $C_1 = \frac{c_{2|1}^{min}}{R} + \frac{c_{3|1}^{min}}{R^2}$. Substituting the right-hand side of equations (4.4) and (4.5) into the first period habit consumption gives:

$$C_1 \geq \frac{\delta c_1}{R} + \frac{\delta^2 c_1}{R^2} = c_1 \left(\delta / R + \delta^2 / R^2 \right). \tag{4.6}$$

First-period habit consumption, C_1, is the consumption value that people have to save in the first period in order to ensure minimum consumption for the second and third period. Meeting habit consumption is always feasible, if people have access to a risk-free asset, and choose current consumption accordingly. Note that these are minimum constraints. Of course, it is possible that people can consume much more in future periods — depending on the actual realizations of income. The second period maximization problem looks as follows:

$$\underbrace{\max}_{c_2,b_2} V_2^{IG} = \frac{(c_2)^{1-\gamma}}{1-\gamma} \; s.t. \tag{4.7}$$

$$c_{3|2}^{min} \geq \delta c_2. \tag{4.8}$$

The term $c_{3|2}^{min}$ denotes minimum future consumption for period 3, conditional on knowledge in period 2. Unlike in the standard discounted expected utility model, people do not care about future expected consumption, but only about future minimum consumption. The present value of second period habit consumption, C_2, is given by $C_2 = \frac{c_{3|2}^{min}}{R}$. Substituting the right-hand side of equation (4.8) into second period habit consumption gives:

$$C_2 \geq c_2(\delta/R). \tag{4.9}$$

Beside absolute consumption and insurance motives, people also care about their relative position in society. The RG captures the fact that people care about reference consumption, c_t^{ref}. I assume that reference consumption is exogenous and given by average aggregate consumption in society. There are two scenarios: Either, own consumption falls short of (or is equal to) reference consumption and people only pursue the IG, or own consumption exceeds reference consumption in which case people also pursue the AG. Again, people pursue the AG if, and only if: $c_t > c_t^{ref}$. Under the AG people maximize the following value function:

$$\underbrace{\max}_{c_t,b_t,s_t} V_t^{AG} = \frac{\left(c_t - c_t^{ref}\right)^{1-\gamma}}{1-\gamma} + \delta E \frac{\left(a_{t+1|t}\right)^{1-\gamma}}{1-\gamma} \tag{4.10}$$

The term γ denotes the curvature parameter, δ is the discount rate, and $E(a_{t+1|t})$ represents the expected disposable income for $t+1$, conditional on information at t. There are two counter-veiling forces at work. One the one hand, the formation of habit consumption shifts weight to future consumption, and hence, people save more for the future. One the other hand, discounting of future periods shifts weight to current consumption, and hence, people save less for the future. In contrast to the standard inter-temporal utility model, people do not plan ahead on how to allocate future resources to consumption, safe assets, and risky assets — except for the fact that they plan for a minimum amount of future consumption. Rather, people derive value from the expected discounted disposable income (not expected discounted consumption). They leave it to

the future how to use these resources, which avoids full contingent planning. This lowers the complexity of the decision-making process and confirms to the notion of procedural rationality.

4.2.3 Financial Income: Assets and Asset Returns

There are two assets: the risk-free bank account savings, b_t, and risky stock investments, s_t.[8] Bank account savings have a gross return of $R = 1+r$. The net return, r, is assumed to be constant (time-invariant) and non-negative: $r \geq 0$. Hence, the gross return is greater or equal to one, $R \geq 1$. Stock market net returns are stochastic (time-variant) and behave as follows

$$\pi_t = \mu + \sigma z_t \ , \tag{4.11}$$

where μ is the expected net return and σ (standard deviation) represents the sensibility to a normally-distributed random variable, z_t, which implies that $\pi_t \sim \mathsf{N}(\mu, \sigma^2)$. The *realized* gross stock return is time-variant and given by $M_t = 1 + \pi_t$. The *expected* gross stock return is time-invariant and given by $D = 1 + \mu$. The limited liability of corporate entities renders normally-distributed gross stock returns unreasonable. Thus, I assume that the *minimum* realized gross returns are non-negative: $\underline{D} \geq 0$. Moreover, I assume that *expected* stock returns exceed the bank account returns ($D > R$), while bank account returns exceed *minimum* stock returns ($R > \underline{D}$). In summary: $D > R \geq 1 > \underline{D} \geq 0$ and $\mu > r \geq 0 > \underline{\mu} \geq -1$.

4.2.4 Non-Financial Income: Wages and Pension Benefits

4.2.4.1 Wages

To keep things simple, I assume that wages, w_t, grow with a non-stochastic rate, ω, and that both individual wages and aggregate average wages follow the same growth rate:[9]

$$w_t = w_{t-1}(1 + \omega) \tag{4.12}$$

$$w_t^{agg} = w_{t-1}^{agg}(1 + \omega) \ . \tag{4.13}$$

[8] Stock investments are not restricted to a single stock, but might represent a sophisticated portfolio of risky assets.

[9] I am aware that this is a strong assumption. Note that the model's decision preferences allow for wage uncertainty. For the simulations, however, I want to focus on uncertainties at the financial markets. Stochastic wages and general equilibrium feedback are, thus, ignored.

The aggregate average wage is defined as the sum over all individual wages divided by the labor force: $w_t^{agg} = \sum w_t / L_t$. In reality, Welfare States ensure subsistence by providing positive transfer payments, or unemployment benefits. I account for this fact by introducing a *minimum* wage, which is equal to the unemployment benefit. I assume that people do not accept wages below the unemployment benefit. They would simply choose to become unemployed in cases where the wage is smaller than the unemployment benefit. The *minimum* wage for period $t+1$, conditional on information in period t, is given by: $w_{t+1|t}^{\min} > 0$.

4.2.4.2 Pension Benefits

There are two types of pension plans: the defined contribution plan and the defined benefits plan. In defined contribution plans policy-makers choose the contribution rates, while the pension benefits are determined by financial or demographic developments. In defined benefit plans the government guarantees the pension benefits in advance. This typically asks for frequent changes in the contribution rates, in order to meet the promised pension benefits. Otherwise, if contributions are not adjusted accordingly, governments run into debts to finance the promised pension benefits. The majority of industrialized countries has moved to defined contribution (DC) pension plans. Therefore, I focus on defined contribution pension schemes in this paper. In particular, I analyze the fully-funded pension scheme and the non-funded, Pay-As-You-Go (PAYG) pension scheme.

All pension schemes are modeled as sustainable, requiring that aggregated contributions equal aggregated benefits. Hence, there is no need for a governmental budget constraint or a transversality condition. The working-age population provides the pension contributions, p_t. Contributions are modeled as a flat tax on individual wages, which is $p_t = w_t \tau$, with τ being the contribution rate. Pension benefits are denoted by P_t^j, where j denotes the different pension schemes.

A *Pure Pay-As-You-Go Pension Scheme (PPAYG)* is sustainable, if the working population provides the means for the retirees. Thus, sustainability demands that the number of old people times their pension benefits must equal the current labor force times their contributions, which is expressed in the subsequent equation:

$$N_t^o P_t^{PPAYG} = \sum w_t \tau = L_t w_t^{agg} \tau = N_t^y w_t^{agg} \tau \left[2+n/1+n\right] \ . \tag{4.14}$$

Dividing by N_t^o and making use of equations (4.1) and (4.2), helps to obtain the equations for the benefits in period t.

$$P_t^{PPAYG} = w_t^{agg} \tau (2+n)(1+n) \tag{4.15}$$

The pension benefit of the PPAYG system depends on the population and aggregate wage growth rate. Clearly, the pension benefits of a retiree in period t, do not depend on his earlier contributions in $t-1$ (middle-aged) and $t-2$ (young). Consequently, all retirees would receive the same benefit, independent of their past individual wage profile. This formula makes only sense in a representative agent framework. In reality, where income is heterogeneous, a pension scheme that provides equal pensions to all retirees would be deemed as extremely unfair.

To accommodate this fact, I modify the pension formula, so that an individual's past wages (w_{t-1}, w_{t-2}) are important for subsequent pension claims. Thereby, I explicitly account for income heterogeneity. Consequently, I refer to this pension scheme as *Individualized Pay-As-You-Go System (IPAYG)*, which is given by the following equation:

$$P_t^{IPAYG} = w_t^{agg} \tau (2+n)(1+n) \frac{{}^{w_{t-2}}/_{w_{t-2}^{agg}} + {}^{w_{t-1}}/_{w_{t-1}^{agg}}}{2} \ . \tag{4.16}$$

As in the PPAYG, the return of the IPAYG depends on the development of aggregate wages and population growth. The difference is that the IPAYG formula accounts for individual wage differences. In fact, the IPAYG system — although very stylized — captures important features of the actual pension formula in Germany.[10]

Contrary to the PAYG schemes, in a *Fully-Funded Pension Scheme (FF)*, the working generation does not pay for the retirees. Rather, each individual contributes to its own pension fund, as long as it is working. When retired, it receives the pension benefit

$$P_t^{FF} = w_{t-2} \tau R_{FF}^2 + w_{t-1} \tau R_{FF} \ , \tag{4.17}$$

with R_{FF} being the fund's financial return. People can decide on the asset they want to invest in: risk-free bank account savings, risky stocks, or a hedged portfolio. The return of the FF scheme depends on financial market developments.

[10] The German pension system is sketched in the appendix. An important difference to the model version is the contribution ceiling that is implemented in reality: at a certain income level, high income earners are no longer required to make further contributions to the system.

4.2.5 Constraints

4.2.5.1 External Constraints

Each individual faces the following budget constraints.

$$a_1 = w_1(1-\tau) = c_1 + b_1 + s_1 \tag{4.18}$$
$$a_2 = w_2(1-\tau) + b_1 R + s_1 M_2 = c_2 + b_2 + s_2 \tag{4.19}$$
$$a_3 = P_3 + b_2 R + s_2 M_3 = c_3 \tag{4.20}$$

The term a_t represents disposable income, which is the sum of financial and labor income, after taxes. There is no inheritance, and thus, initial wealth is equal to zero ($a_0 = 0$). Due to the stochastic stock returns the budgets are random. Moreover, individuals face two financial constraints: a borrowing and a short-selling constraint. People can borrow against future minimum income. This means they are allowed to hold negative bank account savings or to receive credits. In contrast, short-selling of stocks is prohibited.[11]

$$b_1 \geq -\left[w_{2|1}^{min}/R + w_{3|1}^{min}/R^2\right] \tag{4.21}$$
$$b_2 \geq -\left[w_{3|2}^{min}/R\right] \tag{4.22}$$
$$s_1 \geq 0 \ , \ s_2 \geq 0 \tag{4.23}$$

4.2.5.2 Internal Constraints

The consumption habit, C_t, is an endogenous, self-imposed constraint that reflects individuals' precautionary savings motive. Individuals reach the IG, whenever total savings plus discounted future minimum income are greater than (or equal to) the consumption habit. For the first period this implies: $b_1 + s_1 + {}^{w^{\min}_{2|1}}/_R + {}^{w^{\min}_{3|1}}/_{R^2} \geq c_1\,(\delta/R + \delta^2/R^2)$. For the second period this implies: $b_2 + s_2 + {}^{w^{\min}_{3|2}}/_R \geq c_2\,(\delta/R)$. Since the minimum return on bank account savings is higher than the minimum return on stock savings, people use the bank account to reach the IG. To simplify expressions, I define $A_1 \equiv (\delta + \delta^2/R)$, $A_2 \equiv \delta$, $W_1 \equiv w_{2|1}^{min} + w_{3|1}^{min}/R$, and $W_2 \equiv w_{3|2}^{min}$. Then, re-writing yields the following constraints for the first and second period, respectively.

[11] This is a common assumption in the life-cycle investment literature (Cocco et al. (2005)). Moreover, in reality most people have no direct access to short-selling contracts.

$$b_1 R \geq c_1 A_1 - W_1 \tag{4.24}$$
$$b_2 R \geq c_2 A_2 - W_2 \tag{4.25}$$

Once people get sufficiently rich, they can meet the IG and the RG. That is, their own consumption is larger than the reference consumption. If this happens, they also pursue the AG. This implies that total savings can consist of bank account savings and stock investment, which leads to the following constraints:

$$b_1 R + s_1 \underline{D} \geq c_1 A_1 - W_1 \tag{4.26}$$
$$b_2 R + s_2 \underline{D} \geq c_2 A_2 - W_2. \tag{4.27}$$

In contrast to equations (4.24) and (4.25), the above constraints include stock investment. Note that people consider the minimum return on stocks. Even if people start to invest in stocks their most important goal remains to insure habit consumption. Therefore, they have to consider the worst-case return on stocks, when evaluating total savings.

4.2.6 How To Solve the Model

I solve the first period behavior with a three-step procedure that corresponds to the three hierarchic goals. In step 1, people maximize the objective function (4.3), subject to the constraints (4.18) and (4.24) (with $s_1 = 0$).

$$\underbrace{\max}_{c_1, b_1} V_1^{IG} = \frac{(c_1)^{1-\gamma}}{1-\gamma} \; s.t.$$
$$b_1 R = A_1 c_1 - W_1$$
$$c_1 + b_1 = w_1(1-\tau)$$

Subsequently, in step 2, they determine whether the RG is feasible. If $c_t \leq c_t^{ref}$, step 1 describes behavior completely; otherwise, step 3 is triggered. Under step 3 agents maximize the objective function (4.10), subject to the constraints (4.18), (4.23), and (4.26).

$$\underbrace{\max}_{c_1,b_1,s_1} V_1^{AG} = \frac{\left(c_1 - c_1^{ref}\right)^{1-\gamma}}{1-\gamma} + \delta E \frac{\left(a_{2|1}\right)^{1-\gamma}}{1-\gamma} \; s.t.$$
$$b_1 R + s_1 \underline{D} = A_1 c_1 - W_1$$
$$c_1 + b_1 + s_1 = w_1(1-\tau)$$
$$s_1 \geq 0$$

The second-period solution procedure follows the same routine.

4.2.7 Analytical Solutions

First Period Solution: If $Z_1(Rw_1(1-\tau)+W_1) - X_1(A_1+R) \leq c_1^{ref}(A_1+R)$, then the first-period solution is given by

$$c_1 = (w_1(1-\tau)R + W_1)/(A_1+R) \tag{4.28}$$
$$b_1 = (A_1 w_1(1-\tau) - W_1)/(A_1+R) \tag{4.29}$$
$$s_1 = 0 \; , \tag{4.30}$$

otherwise by

$$c_1 = (X_1 + c_1^{ref})/Z_1 \tag{4.31}$$
$$b_1 = \frac{[(X_1 + c_1^{ref})/Z_1](A_1 + \underline{D}) - W_1 - w_1(1-\tau)\underline{D}}{R - \underline{D}} \tag{4.32}$$
$$s_1 = \frac{Z_1(Rw_1(1-\tau)+W_1) - X_1(A_1+R) - c_1^{ref}(A_1+R)}{Z_1(R-\underline{D})} \; , \tag{4.33}$$

where

$$X_1 = (\frac{\delta\theta_1}{R-\underline{D}})^{-1/\gamma}(\frac{w_1(1-\tau)R(D-\underline{D}) + W_1(D-R) + E_1 w_2(1-\tau)(R-\underline{D})}{R-\underline{D}})$$
$$Z_1 = (1 + \frac{\theta_1}{R-\underline{D}}(\frac{\delta\theta_1}{R-\underline{D}})^{-1/\gamma})$$
$$\theta_1 = [D\,(A_1+R) - R\,(A_1+\underline{D})] \; .$$

Proof First Period: The proof follows from the stock investment expression in equation (4.33) and the short-selling constraint in equation (4.23). The denominator of equation (4.33) is positive, as $Z_1 > 0$ and $R > \underline{D}$. The nominator is only positive if the first term is larger than the second and third term. Otherwise, the short-selling constraint becomes binding and stock investment is set equal to zero. In this case, consumption and bank account savings are determined by equations (4.28) and (4.29), respectively.

Second Period Solution: If $Z_2(Ra_2 + w_{3|2}^{min}) - X_2(\delta + R) \leq c_2^{ref}(\delta + R)$, then the second-period solution is given by

$$c_2 = (a_2 R + w_{3|2}^{min})/(\delta + R) \tag{4.34}$$
$$b_2 = (\delta a_2 - w_{3|2}^{min})/(\delta + R) \tag{4.35}$$
$$s_2 = 0 \ , \tag{4.36}$$

otherwise by

$$c_2 = (X_2 + c_2^{ref})/Z_2 \tag{4.37}$$
$$b_2 = \frac{[(X_2 + c_2^{ref})/Z_2](\delta + \underline{D}) - w_{3|2}^{min} - a_2\underline{D}}{R - \underline{D}} \tag{4.38}$$
$$s_2 = \frac{Z_2(Ra_2 + w_{3|2}^{min}) - X_2(\delta + R) - c_2^{ref}(\delta + R)}{Z_2(R - \underline{D})} \ , \tag{4.39}$$

where

$$X_2 = (\frac{\delta\theta_2}{R - \underline{D}})^{-1/\gamma}(\frac{a_2 R(D - \underline{D}) + w_{3|2}^{min}(D - R) + E_2 P_3(R - \underline{D})}{R - \underline{D}})$$
$$Z_2 = (1 + \frac{\theta_2}{R - \underline{D}}(\frac{\delta\theta_2}{R - \underline{D}})^{-1/\gamma})$$
$$\theta_2 = [D\,(\delta + R) - R\,(\delta + \underline{D})] \ .$$

Proof Second Period: The proof follows from the stock investment expression in equation (4.39) and the short-selling constraint in equation (4.23). The denominator of equation (4.39) is positive, as $Z_2 > 0$ and $R > \underline{D}$. The nominator is only positive if the first term is larger than the second and third term. Otherwise, the short-selling constraint becomes binding and stock investment is set equal to zero. In this case, consumption and bank account savings are determined by equations (4.34) and (4.35), respectively.

In order to derive practical recommendations from the analytical solutions, it is necessary to feed the model with real-life data and sensible parameters. This is done in the subsequent sections.

4.3 Parametrization

I take the parameters from the literature or calculate them with German data. All variables that are measured in Euro, such as consumption, savings, and income are expressed in real terms, that is, in 2011 prices. Hence, price changes are not explicitly modeled. All baseline parameters are summarized in table 4.1. The result section contains robustness checks for interesting deviations from the baseline.

Discount Factor and Minimum Consumption Share – δ: It is common to set the annual time preference parameter equal to 0.96 in life-cycle studies (Campbell et al. (2001)).

Effective Pension Contribution Rate – τ: In reality, not everyone is obliged to pay pension contributions. Thus, I adjust the data accordingly. I obtain the effective contribution rate by multiplying the participation rate with the legal contribution rate in Germany. The participation rate is the quotient of people contributing to the pension scheme and the total labor force. The German government devises the contribution rate; sometimes the rate was changed. Taking the average over the annual contribution rates, from 1991 to 2008, gives an effective contribution rate of 0.17; see table C.1.

Population Growth Rate – n: According to a forecast by Statistisches Bundesamt (2006), the German population will decline in the future. In particular, the forecast suggests that the population will shrink to 68.74 million until 2050 — making certain assumptions on life expectancy, net migration, and birth rates (variant 1, p. 64). Taking the current (2013) population of 81.73 million, this indicates a negative growth rate of -0.158, which implies an average annual decline of roughly 0.00467.

Wage Growth Rate – ω: Table C.2 shows the yearly nominal gross wage for Germany between 1991 and 2008. It also contains a deflator, to transform nominal wages to real wages. Assuming that the current trend sustains, the annual wage growth rate is approximately 0.011.

Financial Returns and Their Fluctuation – R, D, $\underline{D}$, σ: According to Deutsche Bundesbank (2001), the annual real interest rate was on average 1.02 between 1961 and 2000. There was a sharp increase after the German reunification, however, this jump ebbed away fast. So adopting the long-term average does not distort the analysis. German citizens are free to choose from most stocks from all over the world. Therefore, an

average return for global financial markets provides a useful benchmark value. According to Campbell and Viceira (2002), the expected net stock return is 0.06 (expected gross stock return is 1.06), with a standard deviation of 0.157. In the worst possible case, a stock portfolio loses its entire value. That is, the minimum net return is minus one, and consequently, the minimum gross return is zero.

Reference Level of Consumption – c_t^{ref}: According to Statistisches Bundesamt (2010b), the average single-person household spends 16,968 Euro on consumption. This number is used, because the model focuses on individuals or single-person households. The reference level of consumption is likely to change over time, since it reflects the average consumption in society. If average wages grow, average consumption follows, and hence, reference consumption grows as well. Hence, I assume that the reference consumption level grows by the same rate as average wages.

Minimum Wage Income – w^{min}: I assume that people with jobs do not earn less than the unemployed. Otherwise they could demand flexible benefits from the German government. The minimum income of the unemployed (Arbeitslosengeld II, Hartz IV) is 364 Euro per month. This number, however, does not reflect that the government covers the cost for flats, children, and further special demands. The Bundesagentur für Arbeit (2010b) estimates that an unemployed single-person receives a minimum income of 801 Euro per month, if direct and indirect costs are considered. Hence, the minimum income, ($w_2^{\min}$), amounts to 9,612 Euro per year. Germany does not guarantee minimum pension benefits. The government does, however, guarantee the subsistence level ("Grundsicherung") by another governmental redistribution system. The subsistence level, or minimum payments amounts to 595 Euro per month.[12] Hence, the minimum available income that is provided by the government during retirement equals 7,140 Euro (595*12).

Curvature Parameter – γ: For the curvature parameter, I choose a value that provides a good fit between the model's predictions and the empirical regularities. A too high value, for instance, would crowd out stock investment in the first period for all agents — even if extremely rich. Contrary, a too low value would generate stock market participation for all income groups — even for low income earners. I set the value to 0.55, such that young people only invest in stocks if they earn more than twice as much as the median income. This corresponds to the idea that only very well-earning people invest in risky asset while young.

[12]Note that the provision of a minimum amount of money during retirement constitutes a small defined benefit component. Technically and judicial this is, however, not part of the governmental pension system. If it would be part of the pension system, the pension formula would become more complex, in order to avoid non-sustainability. Since it is not part of the pension system, though, it does not violate the model's equations.

Table 4.1: Baseline Parameterization (Annual)

Parameter	Symbol	Value
discount factor and minimum consumption share	δ	0.96
effective contribution rate	τ	0.17
wage growth rate	ω	0.011
population growth rate	n	-0.00467
risk-free gross interest rate	R	1.02
expected gross stock return	D	1.06
minimum gross stock return	$\underline{D}$	0
mean of net stock return	μ	0.06
standard deviation of stock return	σ	0.157
reference consumption	c_1^{ref}	16,968 Euro
minimum wage income, workers	w_2^{min}	9,612 Euro
minimum pension income, retirees	w_3^{min}	7,140 Euro
curvature parameter	γ	0.55

4.4 Simulation Results

Note that there is no aggregation over individuals. Rather, I present results for people with different income. In the benchmark scenario all stochastic realizations take on their expected value. Furthermore, this section presents simulations for the IPAYG scheme, because it bears the closest resemblance to the pension scheme that is currently implemented in Germany (see appendix). I start with the minimum annual wage income (9,612 Euro) and simulate in 2,500 Euro steps, up to a relatively high income (164,612 Euro). Note that 164,612 Euro is slightly more than five times the median income. The simulations cover an annual income spectrum of 155,000 Euro, thereby representing the income range of the vast majority of Germany's population. Remember that one model period corresponds to 20 years. Therefore, all annual values and parameters are scaled up accordingly.

4.4.1 Positive Analysis: Empirical Regularities and Model Performance

Figures 4.1 and 4.2 present the simulation results for consumption and asset allocation during working age. The results are compared to the stylized facts in the data and to the predictions of the buffer-stock model (BSM). Table 4.2 provides a short summary. Essentially, the figures demonstrate how people that differ in income display different asset allocation patterns.

Before I describe the results in more detail, I define some terms: Total periodic

savings are the sum of the respective period's bank account and stock savings.[13] The savings rate is defined as total periodic savings relative to the periodic disposable income, formally: $sr_t = (s_t + b_t)/(a_t)$. Periodic disposable income is defined as $a_t = w_t(1-\tau) + b_{t-1}R + s_{t-1}M_t$, which is the sum of after-tax labor income and financial income. The equity share is defined as periodic stock savings relative to total periodic savings: $es_t = s_t/(s_t + b_t)$. The consumption-income ratio is defined as consumption relative to periodic disposable income: $cr_t = c_t/(a_t)$. For all plots blue stars corresponds to the young people (25-44), whereas red diamonds correspond to the middle-aged people (45-64). The x-axis shows the total periodic after-tax income (after paying the pension contribution). The y-axis shows assets, consumption, or ratios, depending on the specific sub-plot. Both axes are measured in Euro.

A first stylized fact is that savings increase with income and age. Subplot 1 of figure 4.1 shows that the model can replicate these features. The data points for both young and middle-aged people are increasing with income. Also, the savings for the middle-aged are higher than for the young, at the same income level. The young are more concerned with consumption: this is reflected in higher absolute consumption (see subplot 4 of figure 4.1) and a higher consumption ratio (see subplot 3 of figure 4.1) compared to the middle-aged. According to Gourinchas and Parker (2002) and Fernandez-Villaverde and Krueger (2007) the BSM can also explain the saving variations that are due to age and income.

A second empirical regularity is that saving rates tend to increase with income, in a given period. This implies that savings grow over-proportionally in income. The model's prediction matches this fact, as can be seen in figure 4.2, subplot 1. The saving rates for the young and middle-aged clearly depict an upward slope in income. Carroll et al. (2000) and Dynan et al. (2004) point out that the BSM is less successful in explaining the saving rates pattern.

A third stylized fact is that stock market participation is income-dependent and age-dependent. Typically, low-income individuals avoid stocks, while high-income individuals invest in stocks. Moreover, individuals with medium-income avoid stocks in their youth, but start to invest with increasing age. The intuition behind these empirical facts is that uncertainty decreases with age. Thus, middle-aged people face less uncertainty than the young, and consequently, invest more rigorously into the risky asset. Figure 4.1, subplot 3, illustrates the model's ability to match these empirical findings. Up to a certain point, both the young and middle-aged have no stocks — reflecting that low-income individuals do not invest in risky assets. Stock investment for the middle-aged occurs around 700,000 Euro ($0.7 * 10^6$). Remember that the numbers are scaled up for 20 years,

[13] Note that these are flow variables, not stock variables.

Figure 4.1: Baseline Simulation: Asset Allocation and Consumption

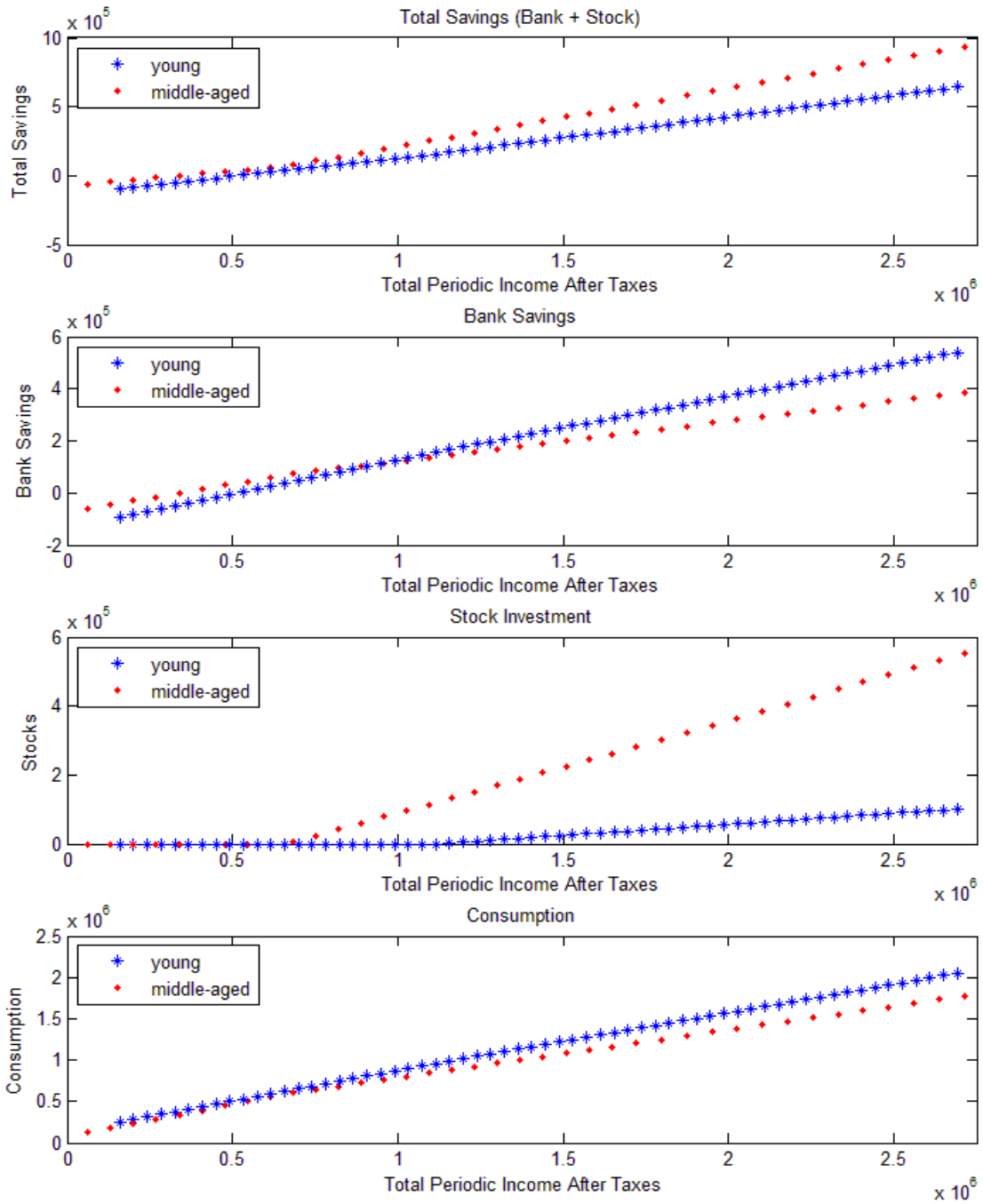
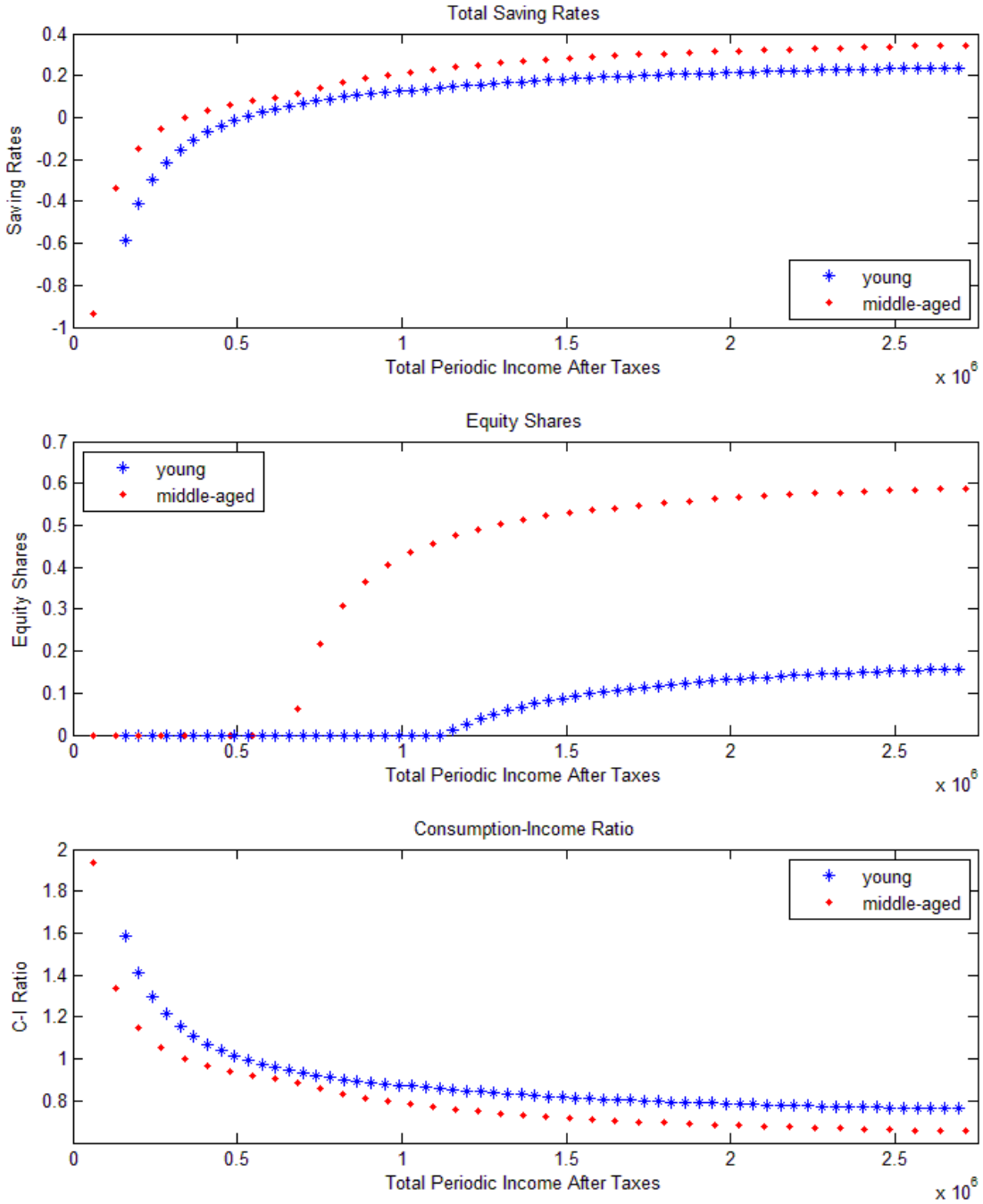


Figure 4.2: Baseline Simulation: Saving Rates, Equity Shares, and Consumption Ratios



so that 700,000 Euro correspond to 35,000 Euro per year. The stock market participation of a young person occurs only at a much higher income. Also, the stock investment pattern of a middle-aged person is much steeper. If people are sufficiently rich, they invest independently of their age. According to Carroll (2002), the BSM cannot replicate the income and age-dependent patterns. It rather suggest that all people invest in stocks, under the premise that expected stock returns exceed those of the bank account.

A fourth empirical regularity is that equity shares increase with working age, once stock market participation has occurred. Also, given a particular age, equity shares rise with income. Subplot 2 of figure 4.2 makes clear that the model's predictions are in line with the empirical facts. In particular, the equity shares of the middle-aged are much higher than those of the young, when considering the same income. Clearly, given the same age, the equity shares are upward-sloping in income. The BSM cannot explain the behavior of equity shares. In stark contrast to the data, it states that — conditional on stock market participation — equity shares are high for the young and declining with working age (Cocco et al. (2005)).

Finally, note the composition of savings. Given the same income, the middle-aged have higher savings at all points. For low and moderate income, they also have higher bank account savings. Once, they become richer, there is a shift in the asset composition. The bank account savings of the middle-aged fall below those of the young, while stock investment is taking off fast.

The results demonstrate that this model outperforms the BSM with respect to the empirical regularities of asset allocation. Note that I made only qualitative comparisons between data and model performance. The main goal was to predict the behavioral patterns correctly. Given its stylized character, I refrain from making quantitative predictions, or to evaluate measures of fit. For quantitative evaluations a fully-fledged multiple-period model with housing, human capital, family composition, and stochastic wages should be used.

4.4.2 Normative Analysis: Evaluation of Pension Schemes

Most economic work uses the rational choice maximization paradigm for both positive and normative analysis. In this paper, the positive model uses non-standard decision rules, and people are heterogeneous with respect to income.

There are three positions in the economic literature, concerning the match between positive and normative analysis (Bernheim and Rangel (2007)). The first position is that normative analysis is only possible, if the normative and positive model share the same structural form and the same parameter values. An example is the rational choice benchmark model that describes behavior and is also used to evaluate behavior. A second

Table 4.2: Stylized Facts and Model Performance

Stylized Facts	**Model Predicts?**	
	BSM	this model
Savings		
1) increase with working age	yes	yes
Saving Rates		
2) increase with income, in a given period	no	yes
Stock Market Participation		
3) low-income persons do not hold stocks	no	yes
4) high-income persons typically hold stocks	yes	yes
5) young, medium-income persons avoid stocks	no	yes
6) middle-aged, medium-income persons hold stocks	no	yes
Equity Shares		
7) increase with income, in a given period	no	yes
8) increase working age	no	yes

position suggests that normative and positive models should have the same structural form, but might differ in their parameter values. The hyperbolic discounting model is an example thereof. For positive preferences (choices) the short-run discount factor — reflecting a present-bias or desire for immediate gratification — is below one, whereas it is set equal to one for normative preferences (real tastes). Third, some authors make a case for divergent positive and normative models — especially after the surge of behavioral economics. Sen (1989), for instance, suggests a capability approach and Sudgen (2004) suggests an opportunity approach. The major problem is that arbitrariness and the potential role for paternalism increase, if the structural form or parameter values of positive and normative models drift apart. This issue should be taken seriously. Therefore, it is not advisable to use the standard utility model to evaluate the decisions that arise from the descriptive model of this paper. Rather, I use the same preferences that guided the positive behavior for the normative evaluation.

Aggregation of individual well-being to social welfare, constitutes many well-known problems of welfare economics. For example, Arrows impossibility theorem, the specific function of the welfare criterion, and the weights with which individuals enter the aggregate function. Hence, I ignore aggregation and focus on the well-being of specific income groups that represent a broad spectrum of the income distribution. The evaluation is based on two metrics: minimum and expected life-time value. In particular, I consider 10 income classes: minimum income, the four borders between the five income quintiles, the median, the mean — shown in table 4.3 — and additionally rich people with twice, thrice, and five times the median income.

Table 4.3: Specific Points Along the German Income Distribution

Minimum	1|2	2|3	Median	3|4	Mean	4|5
9612	20388	28536	32112	35988	42528	47916

The expressions 1|2, 2|3, 3|4, and 4|5 represent the borders between the respective income quintiles.
Source: Bundesagentur für Arbeit (2010a)

4.4.2.1 Construction of Life-Time Value

This section evaluates the consumption decisions that arise from the descriptive part of the paper. The IG is infinitely more valuable than the remaining goals. Due to the risk-free asset (bank account) the IG is always reached. This feature allows me to evaluate an overall value function that considers all three hierarchic goals. The procedure is very much in line with standard proceedings under expected utility. One difference is that the present value function is kinked at the reference value. But, this also happens with other threshold models. A second difference is that the sub-value functions have a different structural form than mainstream models, and do not only change the value of certain structural parameters. The overall periodic value function is given by:

$$V_t = \begin{cases} V_t^{IG} & \text{if } c_t \leq c_t^{ref} \\ V_t^{IG} + V_t^{AG} & \text{if } c_t > c_t^{ref} \end{cases}. \tag{4.40}$$

Below reference consumption, when only the IG is reached, the overall periodic value function equals V_t^{IG}. Above reference consumption, additional value is derived from the AG. Of course, the value from the higher-ranked IG still matters once the RG and AG become attainable. Hence, the sub-values (value below and above average consumption) add up to the overall periodic value function: $V_t = V_t^{IG} + V_t^{AG}$. Note that the different goals are no substitutes, but their value functions can be aggregated, because the people always meet the insurance goal. The formulas for the sub-value functions were given in equations (4.3) and (4.10).

The shape of the overall periodic value function is depicted in figure C.1; see appendix. Sub-plot 1 shows how the value function is shaped, depending on consumption, for a young person. Sub-plots 2 and 3 do the same for a middle-aged and old person, respectively. The value function is concave in consumption and kinked at the reference level. After the reference consumption level is reached, the slope is once again increasing. Intuitively, this reflects the fact that people benefit (or derive value) from living an above-average life style.[14] The further away people get from the reference level, the more

[14] Here, life style is expressed in terms of consumption. Of course, there are more determinants that influence a person's life style in reality.

this *living-above-average-effect* diminishes. For illustrative purposes consider a person that consumes slightly above average. Certainly, this person is very happy that he or she crossed the point of being average. But this effects fades when the person becomes richer and richer. People derive value from consumption, and if applicable from the future opportunity set, in each period. Summing up these periodic values over the life-cycle yields the life-time value function:

$$LV = \sum_{1}^{T} V_t = V_1 + V_2 + V_3 \ . \tag{4.41}$$

The life-time value function consists of three periods ($T = 3$) in this model: the value of the young, middle-aged, and retirees. There is no need for discounting, since discounting was already part of the periodic value functions. Sub-plot 4 of figure C.1 (appendix) shows the shape of the life-time value function. The three kinked locations stem from the summation of the three periodic value functions.

4.4.2.2 Comparison of Pension Schemes

Stochastic Returns Take on Their Expected Value At first, I run simulations for the ex-post case, in which the stochastic stock returns take on their expected value. The results are presented in table 4.4. The first column presents the income classes that are investigated. I choose a representative overview of the income distribution, ranging from people with minimum income up to very rich people, who earn five times as much as the median. The second column gives the numerical values for each income class, that is, how much these people earn. Columns 3 to 5 present the life-time value for the IPAYG, risk-free FF, and risky FF scheme, respectively.

People can choose between the risk-free bank account and the risky stock investment for the internal return of the FF scheme. The FF scheme with risk-free return dominates the IPAYG at all income levels. The FF scheme with risky returns dominates all other schemes. If the stochastic stock returns are equated with their expected value the pension recommendation is trivial, but not very insightful: all people benefit from a FF pension scheme with high risky returns.

Stochastic Stock Returns The question is whether, and how, the pension recommendation is affected if stock returns are truly random, according to equation (4.11). The fluctuations can get very sizable. Remember that people explicitly plan for the expected and worst-case scenario in this model. After they observe the realization of the random variable (stock return), they adjust their behavior in line with the realized

Table 4.4: Life-Time Value for Different Pension Schemes: Non-Stochastic

Income Class	Income	IPAYG	FF risk-free	FF risky
minimum	9612	1601	1601	2210
1|2	20388	2753	2894	4096
2|3	28536	3700	3848	5208
median	32112	3995	4269	5548
3|4	35988	4538	4728	5864
mean	42528	5228	5341	6324
4|5	47916	5618	5721	6657
2*median	64224	6521	6618	7508
3*median	96336	7866	7966	8843
5*median	160560	9750	9864	10804

available budget. It is possible that people with a higher income end up worse (lower life-time value) than people with lower income. This is because they invest more money in risky assets. If the stock return turns out badly, total savings can be significantly lower.

I run 1,000 rounds of stochastic simulations, and afterward, compute the average value for each pension scheme under consideration. This is reported in table 4.5. Each simulation round can be interpreted as follows: There are 1,000 people of the same income class. Every person invests in a different risky stock portfolio. The expected value is the same for each of these stock portfolios. Some portfolios deliver returns above expectations, other portfolios deliver returns below expectations. The same procedure is conducted for all 10 income classes of consideration.

The *average life-time value* of the risk-free FF scheme is at least as high as, or higher than the life-time value of the IPAYG scheme. Only for the minimum income class the life-time value is the same (1,334). This can be explained by the governmental minimum provision of money, if the accumulated pension benefit falls below the subsistence level ("Grundsicherung"). Basically, a person with minimum income gets the same pension benefit in both pension schemes (IPAYG and risk-free FF). The average life-time value of the risky FF scheme dominates both the IPAYG and the risk-free FF for all income groups.

Table 4.6 reports the *minimum life-time value* (of 1,000 simulation rounds) for different pension schemes. Basically, I perform the same random stock return simulations as above and then pick the minimum outcome for each income group. When evaluating the minimum life-time value, the risky FF scheme is dominated by the other schemes. The value for the minimum income group is the same for all three pension schemes. This

Table 4.5: Average Life-Time Value: 1000 Stochastic Simulations

income class	income	IPAYG	FF	FF
			risk-free	risky
minimum	9612	1334	1334	1899
1|2	20388	2514	2612	3441
2|3	28536	3700	3848	5094
median	32112	3995	4269	5442
3|4	35988	4464	4728	5884
mean	42528	5202	5338	6428
4|5	47916	5589	5711	6696
2*median	64224	6495	6602	7591
3*median	96336	7831	7929	8876
5*median	160560	9715	9825	11055

has the same reason as above: the government provides enough money to meet the subsistence level, if the pension benefit would be below this subsistence level. Apparently, the risk-free FF scheme still dominates the IPAYG scheme.

Table 4.6: Minimum Life-Time Value: 1000 Stochastic Simulations

income class	income	IPAYG	FF	FF
			risk-free	risky
minimum	9612	1334	1334	1334
1|2	20388	2514	2612	2447
2|3	28536	3700	3848	3514
median	32112	3983	4269	3779
3|4	35988	4244	4726	4014
mean	42528	4871	5225	4363
4|5	47916	5286	5554	4737
2*median	64224	6099	6347	5606
3*median	96336	7266	7525	6879
5*median	160560	8942	9229	8730

The main insight from tables 4.5 and 4.6 is that the risk-free FF scheme is always at least as good as, or better than the IPAYG scheme — given the baseline parameters.

4.4.3 Robustness

The baseline parameters were chosen very carefully. Nevertheless, it is important to check whether the model holds for reasonable deviations from the baseline. In particular, I vary the three parameters that determine the pension returns: population growth, wage growth, and financial market returns.

In the baseline scenario I considered a negative population growth for Germany. Now, I investigate the case of a population that remains constant, that is, a population growth rate of zero. Positive population growth is extremely unlikely for Germany. In fact, considering that the population does not shrink is already a strong assumption, but works well as an upward bound. Compared to the baseline, a higher population growth increases the return of the PAYG system. A population growth rate of zero leaves the results unaffected; the FF scheme still dominates the PAYG scheme (not reported).

Another important aspect is the growth rate of wages. The wage growth rate is unlikely to grow with the same rate in the future. In addition, simulating a scenario with lower growth rates is not very interesting, as it further reduces the return of the PAYG scheme, which is already dominated by the FF scheme.

Finally, there are the financial market returns. Particularly, the stock return and the bank account return. The stochastic stock market variations were already considered in the previous section and deserve no further attention. I analyze what happens if the risk-free interest rate is lowered, so that the return of the risk-free FF scheme is reduced. I set the real return of the fully-funded pension scheme, R_{FF}, to one (net return is zero). This means that the money in the pension account merely remains the same over time, but does not increase (it might increase in nominal, but not in real terms). Note that this only affects the people who want to invest their pension resources in a risk-free asset. The others invest in the risky stock market anyway. If the pension return is one, the PAYG scheme provides higher life-time value than the FF scheme. For a return of $R_{FF} = 1.01$, however, the FF dominates the PAYG scheme. This implies that the FF scheme is the better choice, unless no risk-free asset with a net return of 0.01, or higher, is available. It is reasonable to assume that people can achieve such a low net return over long-term horizons, for instance, through bank account savings or bonds of credible nations. Moreover, the government could provide a guaranteed minimum return asset for the FF system, because it is better suited to hedge at the capital markets than each individual on its own.[15]

A possible inquiry is the question why I consider the life-time value, and not simply

[15] Certain government employees have, for instance, more financial market expertise than common individuals. Moreover, each individual faces fixed costs for capital market transactions. Governments can hedge much cheaper, and hence, could provide an asset with higher returns, since less transaction fees are deducted.

the value of the pension (old-age) period for the comparisons among pension schemes. First and foremost, the aforementioned results do not change, which is shown in tables C.3, C.4, and C.5. More importantly, I argue that there is an important theoretical reason, which is also reflected in the equations of this model: the periods in which the pension contributions are paid, and the period where the benefits are received, are inter-dependent. One the one hand, the current period's income and savings influence the future pension resources. On the other hand, the expectation about future benefits (and discretionary savings) has an effect on the current decisions. The latter point deserves some explanation. If a person recognizes that he or she might already achieve a pretty high amount of resources during retirement, he or she might be more likely to consume more now and save less for the future. Of course, the contrary is also possible. A forward-looking person understands that the pension resources will be very scarce, and hence, he or she decides to consume less today and save more for the future. In that sense, the periods are inter-twined. Consequently, I see it as natural to evaluate the whole life-time value function, rather than just the old-age value function.

4.4.4 Discussion

Unlike Switzerland, where everyone contributes to the pension system, Germany has several occupational groups that are excluded from the pension system. Moreover, there is a contribution ceiling and an upward bound on pension benefits in Germany. In contrast, the model makes no exemption for special occupational groups (the model does not treat different occupations, merely different income) and has no contribution ceiling. Hence, the contributions are proportional to income for the whole income range. This yields much higher resource transfers, since the rich are not released from their obligation at a certain threshold value. Finally, the model has no upper limits for pension benefits. A similarity between the model and reality is that subsistence is provided through minimum governmental transfer payments.

Optimal pension design is complex and covers multi-dimensional criteria. For instance, fairness, efficiency, personal responsibility, sustainability, rent-seeking, and risk-management. It is questionable whether highly redistributive schemes find acceptance in democratic countries. Tausch et al. (2010) show that redistribution — up to a certain degree — is accepted by society, and that inter-generational redistribution (young to old) finds more support than intra-generational transfers (rich to poor). Furthermore, it is not quite clear whether to evaluate pensions based on their worst-case outcome or their average outcome. Apparently, the average perspective in table 4.5 and the minimum perspective in table 4.6 differ considerably.

The preferences in the model account for insurance motives, or the desire to achieve

a certain minimum for the future. Still, it is unclear whether further minimum motives are at work, for instance, a specific replacement ratio between working and retired life.[16] Moreover, it is not quite clear how, or at which point, real people trade various worst-case insurance motives against expected value maximization. For this reason, I investigate two metrics: the minimum life-time value and the average life-time value. Although I cannot conclude that a risky FF scheme is better or worse than the IPAYG scheme, the results suggest that a risk-free FF scheme is superior to a IPAYG scheme — from the risk-management (minimum) and rent-seeking perspective (average). This holds for all investigated income groups.

A FF scheme has four beneficial features: First, it provides higher average and minimum life-time value, as shown above. Second, it is sustainable by construction — own contributions determine own benefits. Third, it fosters personal responsibility, since everybody plans and provides for itself. Finally, it is very flexible, because people can choose between different return structures (risk-free, hedged, risky) within the FF scheme. Under preference heterogeneity, those with higher risk-appetite can invest their public pension funds in stocks, whereas risk-averse people can save risk-free via a bank account. The results hinge on one important assumption, namely that inflation is not eating up nominal returns in the long-run. To ensure this, governments could provide inflation-indexed assets, at least for a single risk-free, low-return asset.

4.5 Conclusion

The existing literature often evaluates pension systems in a representative agent economy with a perfectly rational decision-maker. In reality, people differ considerably in their income. Moreover, their brain is subject to cognitive limitations, which makes them use simplified decision-strategies. Therefore, this paper investigates pension design when agents are heterogeneous in income and have non-standard preferences. This combination leads to different risk-attitudes, and consequently, to different portfolio choice: richer people invest more heavily into risky assets, such as stocks, whereas low-income earners rely on risk-free bank account savings.

It is insufficient to analyze public pension benefits in isolation. Rather, the public pension component and available private savings upon retirement should be evaluated in combination. Intuitively, people benefit from the sum of the available money, not only from the particular share that comes from the government. If the non-pension

[16] Replacement ratio means that people want to pertain a certain share of working life consumption after retirement. Such a replacement ratio could be modeled as an additional insurance goal, or the parametrization of the current insurance goal could be changed for the transition between the middle-aged and old-age period. In practice, the replacement ratio is most likely also income-dependent.

savings that are accumulated over the life-cycle matter for the pension evaluation, they should be modeled appropriately. Savings crucially depend on the returns of risky and risk-free assets. Unfortunately, mainstream economic models predict the life-cycle asset allocation patterns only inadequately, especially with respect to variations in age and income. As a consequence, I use a model with non-standard decision preferences that predicts asset allocation — at least qualitatively — more appropriately. The deviation from the representative agent model is a natural consequence, as the same agent cannot be expected to execute different investment strategies.

I pose two main questions. First, could Germany benefit from a fully-funded pension scheme in the future or should it continue with the non-funded scheme currently in place? Second, is the optimal pension system income-dependent? I find that — given reasonable assumptions on future demographic and financial developments — Germany could benefit from a transition to a fully-funded pension scheme. In addition, the optimal pension scheme is not income-dependent: all income classes would be better off under a FF scheme with a low-return, but risk-free asset. There are several studies that advocate a FF scheme based on a rational choice framework. Although the perspective and methodology in this paper differs, the recommendation stays the same.

This work focuses on German data. For other countries, there may be some numerical variations in income, savings, and consumption. Nonetheless, the main insights with respect to pension design are expected to carry over to other welfare states with low birth rates and increasing life expectancy. The results are subject to two main limitations. First, the results are pegged to the assumption that a risk-free asset with non-negative net returns exists. Second, there is no general equilibrium feedback, but only a partial equilibrium analysis. I envision four directions for future research: First, a concept for the transition from the current pension scheme to the FF scheme. Second, distortions to the time preference and curvature parameter.[17] This might explain why even some of the rich people avoid risky stock investment. Third, a fully-fledged multiple-period model that considers housing, human capital formation, family composition, health shocks, stochastic wages, and stochastic probabilities of dying would lend itself much better to a quantitative assessment of the predictive power of the model. Finally, a transition from a partial equilibrium model towards a general equilibrium analysis that considers capital; accounts for the correlation between aggregate wages and financial returns; and investigates the impact of different pension schemes on economic growth.

[17] An extended model with bounded will-power in form of a hyperbolic habit formation process — bearing close resemblance with the hyperbolic discounting model in discrete time — was also simulated (not reported). The impact is not very sizable compared to the baseline model. The reason is that people in this model are no expected discounted utility maximizers. Consequently, the effects of the arising time-inconsistencies that are due to bounded will-power are relatively small.

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Appendices

Appendix A

Second Chapter

A.1 Further Information

The following gives an alternative assignment of basic and conspicuous consumption in order to check for sensitivity of results. Only goods above 0.65 on the index by Heffetz (2011) are considered conspicuous. This implies that more consumption categories are assigned to basic consumption; the assignment to conspicuous consumption is more restrictive.

- Basic consumption: health care, care for children & elderly, utilities & housing, mortgage, household products, household services, gasoline, food & beverage (home), child education, dining out
- Conspicuous Consumption: leisure & entertainment, sport, personal care & clothing, car-related

The following presents an alternative assignment of materialistic and experiential consumption.

- Materialistic Consumption: utilities & housing, mortgage, household products
- Experiential Consumption: food & beverage (home), personal care & clothing, dining out, leisure & entertainment, sport
- Non-classified: health care, care for children and elderly, child education, gasoline, car-related, household services

Food & beverage at home and personal care & clothing products are now additionally assigned to experiential consumption. For food & beverage at home it can be argued that it is consumed shortly after it is bought. Hence, it does not constitute a possession,

but rather an experience of taste, vision, and smell (same as dining out). Personal care products & clothing might also deliver an experiential value, for instance, the experience of a fragrant perfume. Several consumption products are non-classified. Car-related expenses, for instance, are mostly tangible objects. But still for some people the value of a car comes from the experience of driving it; not from having it and putting it in the garage. For health care and care for children and elderly spending, it can be argued that it is truly neither materialistic nor experiential, but simply a necessary purchase at certain times. Finally, child education could be seen as a pure investment good — not as a consumption good.

A.2 Tables

Table A.1: Linear Fixed-Effects Estimation

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
consumption	0.0230***	0.0178**	-0.0093
	(0.0076)	(0.0076)	(0.0060)
consumption^2	-0.0011**	-0.0008	0.0004
	(0.0005)	(0.0006)	(0.0005)
income	0.0057***	0.0015	-0.0017
	(0.0012)	(0.0009)	(0.0010)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
R-squared	0.0773	0.0969	0.1237
P-Value Wald-Test	0.0000	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls and time effects are not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Consumption Categories and SWB – Linear Fixed Effects

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
food and beverage (home)	0.0373**	0.0337*	-0.0238
	(0.0171)	(0.0189)	(0.0173)
health care (out-of-pocket)	-0.0228**	-0.0253**	0.0150*
	(0.0102)	(0.0115)	(0.0086)
utilities and housing	0.0103	0.0038	-0.0123
	(0.0158)	(0.0153)	(0.0128)
mortgage	-0.0038	0.0027	-0.0016
	(0.0096)	(0.0094)	(0.0072)
personal care	0.0876***	0.0664***	-0.0290*
	(0.0194)	(0.0194)	(0.0165)
household products	0.0235	0.0993***	-0.0580*
	(0.0349)	(0.0365)	(0.0326)
car-related	-0.0397**	-0.0119	0.0116
	(0.0202)	(0.0205)	(0.0181)
gasoline	0.0179	0.0156	-0.0004
	(0.0310)	(0.0317)	(0.0275)
household services	0.0021	-0.0077	0.0203
	(0.0292)	(0.0283)	(0.0260)
child education	0.0102*	0.0039	-0.0068
	(0.0056)	(0.0055)	(0.0049)
care child and elderly	0.0030	-0.0170	0.0308*
	(0.0161)	(0.0179)	(0.0157)
sport	0.0609**	-0.0060	-0.0137
	(0.0280)	(0.0293)	(0.0282)
dining out	0.0735**	0.0805***	-0.0421
	(0.0291)	(0.0293)	(0.0268)
leisure and entertainment	0.0295*	0.0717***	-0.0102
	(0.0168)	(0.0189)	(0.0160)
Controls	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	62978	62977	62980
Adjusted R-squared	0.0777	0.0988	0.1216
Log-Likelihood	-43240	-48461	-38888
Significance	0.0000	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Consumption Ratios and SWB – Ordered Probit

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
food and beverage (home)/C	0.0754	-0.1357	0.1046
	(0.1037)	(0.0966)	(0.0994)
health care (out-of-pocket)/C	-0.1537*	-0.2042**	0.2628***
	(0.0885)	(0.0901)	(0.0882)
utilities and housing/C	-0.0746	-0.1742**	0.0552
	(0.0863)	(0.0826)	(0.0870)
personal care and clothing/C	0.6053***	0.3776***	-0.2724**
	(0.1197)	(0.1084)	(0.1242)
household products/C	0.1420	0.3978*	-0.4459*
	(0.2162)	(0.2325)	(0.2405)
car-related/C	-0.0046	-0.0642	0.1015
	(0.1250)	(0.1165)	(0.1291)
gasoline/C	-0.0192	-0.0777	0.1817
	(0.1464)	(0.1320)	(0.1467)
household services/C	-0.0706	-0.1000	0.2663
	(0.1945)	(0.1887)	(0.2066)
child education/C	0.2470**	0.0019	-0.0625
	(0.1033)	(0.0923)	(0.0962)
care child and elderly/C	-0.0025	-0.1614	0.2736**
	(0.1364)	(0.1239)	(0.1347)
sport/C	0.5895***	-0.1038	-0.0168
	(0.2011)	(0.1954)	(0.2326)
dining out/C	0.4199***	0.2101	-0.2687*
	(0.1515)	(0.1395)	(0.1520)
leisure and entertainment/C	0.3756***	0.3518***	-0.0535
	(0.1329)	(0.1185)	(0.1380)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	62978	62977	62980
Pseudo R-squared	0.1527	0.1779	0.2283
Log-Likelihood	-62131	-65927	-54423
Significance	0.0000	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Consumption Categories and SWB – Without Income Control

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
food and beverage (home)	0.0656**	0.0308	-0.0296
	(0.0317)	(0.0302)	(0.0356)
health care (out-of-pocket)	-0.0491***	-0.0376**	0.0283*
	(0.0157)	(0.0151)	(0.0163)
utilities and housing	0.0212	-0.0137	-0.0093
	(0.0253)	(0.0229)	(0.0256)
mortgage	0.0068	0.0053	-0.0072
	(0.0172)	(0.0142)	(0.0147)
personal care and clothing	0.1371***	0.0948***	-0.0594*
	(0.0324)	(0.0275)	(0.0313)
household products	0.0804	0.1318**	-0.0841
	(0.0617)	(0.0616)	(0.0695)
household services	0.0069	-0.0422	0.0506
	(0.0514)	(0.0433)	(0.0540)
car-related	-0.0646*	-0.0373	0.0240
	(0.0349)	(0.0305)	(0.0361)
gasoline	0.0683	0.0898*	0.0030
	(0.0543)	(0.0502)	(0.0551)
child education	0.0195**	0.0059	-0.0023
	(0.0096)	(0.0078)	(0.0094)
care child and elderly	-0.0186	-0.0462	0.0671**
	(0.0297)	(0.0290)	(0.0317)
sport	0.0995*	-0.0399	-0.0331
	(0.0525)	(0.0466)	(0.0590)
dining out	0.1392***	0.1394***	-0.0929*
	(0.0484)	(0.0439)	(0.0522)
leisure and entertainment	0.0681**	0.0783***	-0.0356
	(0.0299)	(0.0285)	(0.0337)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	70605	70605	69620
Pseudo R-squared	0.1522	0.1762	0.2263
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-69529	-73955	-60201

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Consumption Categories and SWB – Without Subjective Health Controls

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
food and beverage (home)	0.0362	-0.0045	0.0113
	(0.0331)	(0.0312)	(0.0344)
health care (out-of-pocket)	-0.0660***	-0.0606***	0.0602***
	(0.0170)	(0.0159)	(0.0159)
utilities and housing	0.0309	-0.0058	-0.0015
	(0.0257)	(0.0229)	(0.0247)
mortgage	0.0268	0.0307*	-0.0269
	(0.0180)	(0.0176)	(0.0172)
personal care and clothing	0.1391***	0.0901***	-0.0591*
	(0.0341)	(0.0279)	(0.0308)
household products	0.0171	0.0622	-0.0386
	(0.0631)	(0.0654)	(0.0673)
household services	-0.0045	-0.0452	0.0534
	(0.0528)	(0.0448)	(0.0510)
car-related	-0.0418	-0.0293	0.0140
	(0.0378)	(0.0342)	(0.0362)
gasoline	0.0224	0.0412	0.0168
	(0.0556)	(0.0529)	(0.0532)
child education	0.0260**	0.0113	-0.0179*
	(0.0103)	(0.0089)	(0.0103)
care child and elderly	0.0026	-0.0282	0.0536*
	(0.0311)	(0.0299)	(0.0319)
sport	0.0903*	-0.0383	-0.0028
	(0.0509)	(0.0488)	(0.0626)
dining out	0.0913*	0.0849*	-0.0311
	(0.0471)	(0.0438)	(0.0478)
leisure and entertainment	0.0807**	0.1099***	-0.0627**
	(0.0320)	(0.0283)	(0.0311)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	62998	62996	62999
Pseudo R-squared	0.0572	0.0323	0.0353
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-69162	-77636	-68063

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

Compared to baseline model perceived health (health, wornout, sleep issues) is not included.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Basic vs. Conspicuous Consumption – Robustness of Categorization

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-basic	0.0172**	0.0112*	-0.0067
	(0.0068)	(0.0059)	(0.0064)
C-conspicuous	0.0717***	0.0636***	-0.0429**
	(0.0188)	(0.0171)	(0.0194)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
Pseudo R-squared	0.1484	0.1742	0.2264
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-72940	-77221	-63733

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Materialistic vs. Experiential Consumption – Robustness of Categorization

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-materialistic	0.0149	0.0177	-0.0137
	(0.0134)	(0.0124)	(0.0125)
C-experiential	0.1016***	0.0812***	-0.0528***
	(0.0161)	(0.0140)	(0.0160)
Controls	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
Pseudo R-squared	0.1485	0.1739	0.2264
P-Value Wald-Test	0.0000	0.0000	0.0000
Log-Likelihood	-72931	-77244	-63732

Standard errors in parenthesis, clustered on id-variable.

Cut-off variables, controls, and time effects are not reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Different Domain Satisfactions – Ordered Probit

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Satisfaction	income	economic	job	social	health
consumption	0.0679***	0.0508***	0.0421***	0.0416	0.0050
	(0.0122)	(0.0123)	(0.0129)	(0.0341)	(0.0380)
consumption^2	-0.0034***	-0.0025***	-0.0022**	-0.0036	0.0009
	(0.0009)	(0.0009)	(0.0010)	(0.0029)	(0.0031)
income	0.0152***	0.0104***	0.0089***	0.0075	0.0040
	(0.0021)	(0.0018)	(0.0024)	(0.0065)	(0.0078)
Controls	Yes	Yes	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Observations	73227	73225	73231	8744	8743
Pseudo R-squared	0.1230	0.1347	0.1501	0.1351	0.4049
Significance	0.0000	0.0000	0.0000	0.0000	0.0000
Log-Likelihood	-89479	-89439	-78289	-8828	-6240

Standard errors in parenthesis, clustered on id-variable.

Cut-offs, controls, and time effects not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: First-Stage Results of Fixed-Effects IV-Estimation

	(1)	(2)
Dependent Variable:	Consumption	Consumption^2
lag of consumption	0.5974***	1.1417
	(0.0642)	(1.1399)
lag of consumption^2	-0.0449**	0.2223
	(0.0211)	(0.4018)
lag of consumption^3	0.0032	0.0084
	(0.0025)	(0.0491)
lag of consumption^4	-0.0001	-0.0008
	(0.0001)	(0.0018)
income	0.0076***	0.0572***
	(0.0018)	(0.0194)
stocks	0.0072	0.0293
	(0.0137)	(0.1687)
credit card debt	0.0143*	0.1341
	(0.0081)	(0.1071)
home owner	0.0301	0.0558
	(0.0396)	(0.3401)
health insurance	0.0713***	0.3819***
	(0.0201)	(0.1444)
age	0.0745	-0.3967
	(0.0590)	(0.5962)
age^2/100	-0.1187	0.9525
	(0.1125)	(1.1058)
age^3/10000	0.0465	-0.8019
	(0.0682)	(0.6672)
family size	0.0610***	0.4280***
	(0.0124)	(0.1186)
working	0.0479***	0.1773
	(0.0160)	(0.1619)
self-employed	0.0092	0.1547
	(0.0353)	(0.4591)
retired	0.0042	-0.1001
	(0.0259)	(0.2360)
married	0.2869***	1.4171***

	(0.0390)	(0.3076)
education	-0.0016	0.0392
	(0.0361)	(0.3502)
US-State	0.0002	0.0053
	(0.0035)	(0.0321)
health (1-5)	-0.0046	-0.0995
	(0.0083)	(0.0875)
wornout (1-5)	0.0073	-0.0074
	(0.0052)	(0.0644)
sleep issues (1-5)	0.0000	-0.0423
	(0.0063)	(0.0772)
Observations	60506	60506
R-squared	0.1491	0.0865
P-Value Wald-Test	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects are accounted for, but not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Causality of Basic and Conspicuous Consumption – Linear Fixed-Effects IV-Estimation

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-basic	0.0005	-0.0062	0.0049
	(0.0144)	(0.0092)	(0.0121)
C-conspicuous	0.0345*	0.0566***	-0.0273
	(0.0201)	(0.0214)	(0.0185)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	60506	60506	60510
R-squared	0.0779	0.0950	0.1226
P-Value Wald-Test	0.0000	0.0000	0.0000
P-Value Endogeneity Test	0.6728	0.1983	0.7043
P-Value Hansen-J	0.1234	0.1202	0.0900

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects accounted for, but not reported.

First-stage instruments: first-lag polynomials 1 to 4 of basic and conspicuous consumption.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: First-Stage Results of Fixed-Effects IV-Estimation on Basic and Conspicuous Consumption

	(1)	(2)
Dependent Variable:	Basic	Conspicuous
lag C-basic	0.4981***	0.0303
	(0.0766)	(0.0303)
lag C-conspicuous	-0.0100	0.5063***
	(0.0238)	(0.0718)
lag C-basic^2	-0.0129	0.0051
	(0.0407)	(0.0149)
lag C-conspicuous^2	0.0171	-0.0789*
	(0.0128)	(0.0436)
lag C-basic^3	-0.0024	-0.0017
	(0.0074)	(0.0024)
lag C-conspicuous^3	-0.0030	0.0082
	(0.0021)	(0.0082)
lag C-basic^4	0.0003	0.0001
	(0.0004)	(0.0001)
lag C-conspicuous^4	0.0001	-0.0003
	(0.0001)	(0.0004)
income	0.0032***	0.0046***
	(0.0011)	(0.0014)
stocks	0.0088	-0.0038
	(0.0088)	(0.0090)
credit card debt	0.0105**	0.0031
	(0.0051)	(0.0059)
home owner	0.0117	0.0188
	(0.0298)	(0.0211)
health insurance	0.0525***	0.0186*
	(0.0146)	(0.0098)
age	0.1021***	-0.0370
	(0.0324)	(0.0393)
age^2/100	-0.1756***	0.0739
	(0.0628)	(0.0739)
age^3/10000	0.0896**	-0.0528
	(0.0389)	(0.0445)

family size	0.0341***	0.0246***
	(0.0068)	(0.0077)
working	0.0251**	0.0210*
	(0.0111)	(0.0108)
self-employed	0.0080	0.0012
	(0.0220)	(0.0223)
retired	0.0046	-0.0029
	(0.0194)	(0.0147)
married	0.1571***	0.1267***
	(0.0273)	(0.0221)
education	0.0135	-0.0224
	(0.0156)	(0.0278)
US-State	-0.0008	0.0014
	(0.0031)	(0.0011)
health (1-5)	-0.0083	0.0031
	(0.0053)	(0.0057)
wornout (1-5)	0.0057*	0.0009
	(0.0030)	(0.0039)
sleep issues (1-5)	0.0031	-0.0034
	(0.0037)	(0.0046)
Observations	60506	60506
R-squared	0.1997	0.0847
P-Value Wald-Test	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects are accounted for, but not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Basic and Conspicuous Consumption – Linear Fixed-Effects Estimation

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-basic	-0.0013	-0.0016	0.0007
	(0.0056)	(0.0054)	(0.0042)
C-conspicuous	0.0234***	0.0200***	-0.0107***
	(0.0046)	(0.0048)	(0.0040)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
R-squared	0.0775	0.0970	0.1237
P-Value Wald-Test	0.0000	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects accounted for, but not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Causality of Materialistic and Experiential Consumption – Linear Fixed-Effects IV-Estimation

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-materialistic	-0.0104	0.0007	0.0023
	(0.0116)	(0.0114)	(0.0100)
C-experiential	0.4115***	0.3682***	-0.1808**
	(0.0903)	(0.0930)	(0.0824)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	60506	60506	60510
R-squared	0.0642	0.0878	0.1201
P-Value Wald-Test	0.0000	0.0000	0.0000
P-Value Endogeneity Test	0.0004	0.0036	0.1604
P-Value Hansen-J	0.0683	0.0906	0.3609

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects accounted for, but not reported.

First-stage instruments: first-lag polynomials 1 to 4 of materialistic and experiential consumption.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.14: First-Stage Results of Fixed-Effects IV-Estimation on Materialistic and Experiential Consumption

	(1)	(2)
Dependent Variable:	Materialistic	Experiential
lag C-materialistic	0.6192***	0.0105
	(0.0683)	(0.0096)
lag C-experiential	-0.0575	0.2889***
	(0.0727)	(0.0277)
lag C-materialistic^2	-0.0454*	-0.0004
	(0.0243)	(0.0032)
lag C-experiential^2	0.1785	-0.1386**
	(0.1323)	(0.0557)
lag C-materialistic^3	0.0025	0.0000
	(0.0031)	(0.0004)
lag C-experiential^3	-0.0736	0.0393
	(0.0678)	(0.0325)
lag C-materialistic^4	-0.0001	-0.0000
	(0.0001)	(0.0000)
lag C-experiential^4	0.0067	-0.0051
	(0.0097)	(0.0050)
income	0.0056***	0.0022***
	(0.0016)	(0.0005)
stocks	0.0028	0.0052
	(0.0130)	(0.0033)
credit card debt	0.0143*	-0.0005
	(0.0076)	(0.0019)
home owner	0.0338	-0.0059
	(0.0362)	(0.0070)
health insurance	0.0621***	0.0107***
	(0.0188)	(0.0040)
age	0.0729	-0.0054
	(0.0559)	(0.0108)
age^2/100	-0.1213	0.0175
	(0.1057)	(0.0211)
age^3/10000	0.0514	-0.0142
	(0.0637)	(0.0131)

family size	0.0582***	0.0012
	(0.0112)	(0.0022)
working	0.0368**	0.0120***
	(0.0151)	(0.0037)
self-employed	0.0130	-0.0041
	(0.0326)	(0.0078)
retired	-0.0025	0.0071
	(0.0249)	(0.0062)
married	0.2534***	0.0290***
	(0.0363)	(0.0081)
education	-0.0039	0.0023
	(0.0304)	(0.0102)
US-State	-0.0003	0.0005
	(0.0034)	(0.0005)
health (1-5)	-0.0043	-0.0004
	(0.0078)	(0.0020)
wornout (1-5)	0.0103**	-0.0036***
	(0.0047)	(0.0012)
sleep issues (1-5)	0.0006	-0.0007
	(0.0059)	(0.0015)
Observations	60506	60506
R-squared	0.1529	0.0392
P-Value Wald-Test	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects are accounted for, but not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.15: Materialistic and Experiential Consumption – Linear Fixed-Effects Estimation

	(1)	(2)	(3)
Dependent Variable:	Life Satisfaction	Happiness	Depression
C-materialistic	0.0067*	0.0039	-0.0028
	(0.0037)	(0.0037)	(0.0028)
C-experiential	0.0699***	0.0771***	-0.0337***
	(0.0129)	(0.0136)	(0.0118)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes
Observations	73161	73159	73165
R-squared	0.0776	0.0973	0.1238
P-Value Wald-Test	0.0000	0.0000	0.0000

Standard errors in parenthesis, clustered on id-variable.

Controls, fixed effects, and time effects accounted for, but not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Third Chapter

B.1 Literature

B.1.1 Theory

Modigliani and Brumberg (1954) and Friedman (1957) provided path-breaking papers on the permanent income hypothesis life-cycle model (PIH-LCM). The theory describes the saving behavior and consumption smoothing of rational and forward-looking people. However, several aspects in the data — the so-called "puzzles" — could not be reconciled with the PIH-LCM. An important puzzle is the *excess smoothing* of consumption, as noted in Deaton (1987), Campbell and Mankiw (1989), Carroll and Weil (1994), and Shintani (1996). Despite the strong volatility in individuals' income and wealth, the consumption path is remarkably stable. Habituation in consumption serves as a possible explanation. There has been considerable work on habit formation and social comparison following seminal papers by Veblen (1899) and Duesenberry (1949). Fisher (1930) and Hicks (1965) were among the first who criticized the assumption of time-inseparability.

The most notable time-inseparable preferences are durability and internal habits. Durability renders the consumption path lumpy (substitutability in adjacent periods), whereas habit formation makes it smoother (complementarity). The novelty lies in the fact that people *do not* separately evaluate periodic utilities, but display temporally dependent preferences.[1] Most importantly, this mechanism works directly through preferences; and not indirectly, through budget constraints. It is noteworthy that durability might mitigate, or even cancel out the internal habit effect (and vice versa), as it has an opposite effect on utility.

Initial formulations of habit formation are provided in external form. The term "external

[1] The literature uses several different terms to describe time-inseparable preferences, in particular, habit persistence, habit formation, durability, relative consumption, and state-dependence.

habit" was coined by Campbell and Cochrane (1999). Others, such as Pollak (1970), Abel (1990), and Gali (1994), used the same idea, but referred to it as "catching/keeping up with the Joneses". External habits constitute externalities, because people do not consider how their own consumption choice impacts the consumption choice of others.

Algebraically, $U(C_t) = \sum_0^T u(C_i) = u(C_0) + u(C_1) + ... + u(C_T)$, represents time-separability, whereas time-inseparability implies that periodic utilities are somehow inter-twined. *Durable* goods provide a consumption flow for multiple periods

$$C_t^* = C_t + \sum_{i=1}^{\infty} a_i C_{t-i} = (a(L))C_t,$$

in which $a(L) = 1 + \sum_{i=1}^{\infty} a_i L^i$ and $0 < a \leq 1$. That is, consumers derive utility for several periods. For a durable that can be stored only one period, this reduces to the special case $C_t^* = C_t + aC_{t-1} = (1 + aL)C_t$. For a *non-durable* good, in which habitual consumption is assumed, a general utility function looks as follows:

$$u_t = (C_t - b\sum_{j=1}^{\infty} d_j C_{t-j}).$$

The term b represents the "force of habit" $(0 < b \leq 1)$ and d the weighting parameter on different consumption lags. For ease of exposition, I only describe inner utility, without making any assumptions about outer utility. The special case (d=1, j=1), which is predominantly considered in the literature, includes just one lag and can be written as follows: $u_t = (C_t - bC_{t-1})$.

If one considers a durable good that is also habit forming, the matter gets more complicated. Putting together the special cases from above, one can write $u_t = (C_t^* - bC_{t-1}^*)$. Now, substituting in for C_t^* yields:

$$u_t = (C_t + aC_{t-1} - b(C_{t-1} + aC_{t-2})).$$

Clearly, habits (b) have a negative impact on utility, whereas durability (a) has a positive net effect. This is why durability is said to cancel out habit. A solution to the general case is also available, but less instructive.

Authors mostly differentiate between two habit specifications; additive and multiplicative. Let H represent the habit stock, given by $H_t = \rho H_{t-1} + (1 - \rho)C_t$, with ρ being a weighting factor. A utility function with additive habits can be written as follows:

$$u_t = \frac{1}{1-\alpha} \left(C_t - bH_{t-1}\right)^{1-\alpha}.$$

For $\rho = 0$, this reduces to the special case $u_t = (1-\alpha)^{-1} \left(C_t - bC_{t-1}\right)^{1-\alpha}$. Making use of $\Delta C_t = C_t - C_{t-1}$, one can re-write $u_t = (1-\alpha)^{-1} \left((1-b)C_t - \Delta C_t\right)^{1-\alpha}$, which illustrates why utility depends on both; consumption level and consumption growth. Multiplicative habits look as follows:

$$u_t = \frac{1}{1-\alpha} \left(\frac{C_t}{H_{t-1}^{\gamma}}\right)^{1-\alpha}.$$

As before, $\rho = 0$ reflects a special case, hereafter: $u_t = (1-\alpha)^{-1} \left(\frac{C_t}{C_{t-1}^{\gamma}}\right)^{1-\alpha}$. Most studies work with one of these special cases. Occasionally, multiple consumption lags enter in a weighted form.

B.1.2 Findings

The evidence on habit formation is inconclusive, because of strongly varying methodology and data sources among existing studies. Most studies consider either internal, or external habit formation, whereas nested models are rarely used.[2] Studies also use different time frequencies and lag length. Some authors use seasonally adjusted data, others prefer non-adjusted data. In addition, some authors use single-good models, while others employ multiple-good categories. Macro-econometric papers typically provide only time-series evidence, which is less reliable than panel studies. Unlike panel data, aggregate time-series data ignores individual heterogeneity. Furthermore, several different econometric estimation techniques (ordinary least squares, least squares dummy variable, fixed effects, random effects, generalized method of moments) are applied. Finally, data sources of different type are considered (statistical office, survey, retailer, credit card). Hereafter, I summarize important papers, without any claim of exhaustiveness.

- Studies based on Theory

Heal and Ryder (1973) analyze optimal growth models with habits in the general sense (not specifying whether internal or external) and a representative agent. Sundaresan

[2] Some studies allow for a more general preference specification, namely, time-inseparability. They leave it open, whether relative consumption behaves like a substitute (durability) or like a complement (internal habit). Some authors suggest that consumption is durable in the short-run, while habits manifest themselves over the long-run.

(1989) explains the empirically observed excess consumption by employing an internal habit with weighted average past consumption. Abel (1990) considers both habits types in a *multiplicative* preference specification and with a one-lag structure and calculates prices of stocks, bills, and consoles. Constantinides (1990) uses *additive* habit formation, multiple-lags, and exponentially weights on internal and external habits. His theoretical findings implies that the habit coefficient should be about 0.8 to resolve the equity premium puzzle. Deaton (1992) summarizes the whole consumption literature — at that time — and embeds habits in a richer setting of liquidity constraints, long-run convergence, precautionary savings, etc. Gali (1994) investigates external habits (additive) and uses the a-priori more sensible assumption of current, rather than lagged, external habit to discuss optimal portfolio choice and asset prices. Abel (1999) resolves the equity premium puzzle with a 1-lag, external habit model. Campbell and Cochrane (1999) find that an external habit adapts non-linearly to the history of consumption, in an additive setup with one-lag structure. Chan and Kogan (2002) deviate from the representative agent postulation of the above-mentioned studies. They allow for individually varying risk aversion and analyze external habits in a multiplicative setting with infinite moving-average lag structure. Only by combining habit preferences with a diversity of risk preferences, they can replicate various qualitative features of aggregate stock market returns. Wachter (2006) offers a theory of the nominal term structure, which is based on an external, one-lagged, additive habit in a representative agent framework. Dubin et al. (2012) constitutes the only model based on micro-economics and heterogeneity among agents. In this setting, a one-lagged internal habit explains aggregate asset pricing and important financial metrics much better than an external counterpart.

- Studies based on Macro-Econometrics

Dunn and Singleton (1986) use monthly aggregate data and find that time-inseparable preferences explain interest term structures much better than conventional models. They use a two-good model that differentiates between durables and non-durables. Eichenbaum et al. (1988) apply seasonally-adjusted, monthly US aggregate consumption data and find durability rather than internal habit formation. Muellbauer (1988) investigates internal habit formation with quarterly, US aggregate consumption. He rejects the role of *rational habit formation*, but explains the evidence for some kind of persistence by *myopic habit formation*. Eichenbaum and Hansen (1990) employ monthly aggregate time series data and find evidence for internal habits. Furthermore, they suggest that durables and non-durables are substitutes, so that aggregation into a single measure is unproblematic.[3]

[3]Although their findings of perfect substitutability of durables and non-durables is not robust to all specifications, the evidence still supports some type of substitutability over strict separability. In addition, some goods classified as non-durable, display durable behavior, which is explained by different

Ferson and Constantinides (1991) consider seasonally-adjusted, aggregate consumption data with different frequencies, namely, annual, quarterly, and monthly data. They find evidence for internal habit formation. Ferson and Harvey (1992) use unadjusted, quarterly data and find seasonal habit persistence.[4] Heaton (1995) uses monthly US consumption data with infinite lags and obtains mixed results: Durability in the short-run, but habit persistence in the long-run. Fuhrer (2000) uses quarterly data, allows for multiple lags, and concludes that internal habits matter. Both habit forms are considered by Korniotis (2010). He develops a new bias-corrected estimator to deal with the dynamic panel, fixed effects, spatial effects, and endogenous control variables.[5] Moreover, he introduces several refinements for the external habit measure. While rejecting internal habit, he finds significant and sizable (0.34) external habituation. Grishchenko (2010) also investigates both habit types, using quarterly data, and concludes the opposite; evidence for multiple-lag internal habit, but no external habit. Carroll et al. (2011) use quarterly data in 13 countries to compare three alternative paradigms: the random-walk hypothesis by Hall (1978), rule-of-thumb consumers as in Campbell and Mankiw (1989), or the habit-formation hypothesis.[6] Habit formation has the strongest empirical support.

- Studies based on Micro-Econometrics

Meghir and Weber (1996) apply quarterly CEX data (rotating panel) and do not reject time-separability preferences. It is problematic, however, that they cover only four consecutive quarters, which does not allow to properly account for fixed effects. Proceeding like this gives rise to potential spurious correlation (estimation bias) between current and past consumption. In addition to habit preferences, they consider liquidity constraints. They emphasize that borrowing constraints introduce dependence on variables within people's information set, which ultimately invalidates the standard Euler equation. Naik and Moore (1996) account for fixed effects in an annually, one-lagged specification and find evidence for habit formation in food consumption data. One issue, though, is that they do not address the potential endogeneity of the dynamic panel. Dynan (2000) investigates internal habit formation, using annual PSID food consumption data, and rejects the habit-hypothesis.[7] Also, she does not control for potential bias due to

frequencies. A good that is non-durable on the semi-annual frequency can be durable on a monthly basis.

[4] They are guided by Wallis (1974), who finds that seasonal adjustment induces spurious correlation between error and past model values.

[5] This new estimator constitutes a hybrid estimator, combining desirable properties from Hahn and Kuersteiner (2002) and Anderson and Hsiao (1982).

[6] The random-walk hypothesis essentially says that consumption is unpredictable. Rule-of-thumb consumers simply consume their entire income.

[7] She also investigates the robustness of her results by constructing additional non-durable consumption data, merging CEX and PSID data.

unobserved fixed effects. Guariglia and Rossi (2002) obtain consumption expenditures from the British Household Panel Survey (BHPS). They simultaneously check for internal habits and precautionary savings motives on three non-durable goods, namely, food at home, transport, and services. Using annual, one-lagged data habits are rejected in favor of durability. Carrasco et al. (2005) employ quarterly data from the Spanish Continuous Family Expenditure Survey (ECPF) and find mixed results. First, they show that preferences seem time-separable when fixed effects are not controlled for, but non-separable once controlling for heterogeneity and adequate instruments. Second, habit formation is present for food and services, but not for transport. Unfortunately, estimates are unreliable, since at most eight consecutive quarters are available per household (rotating panel). Browning and Collado (2007) use the same data-set as Carrasco et al. (2005) and also find mixed evidence. Some goods are strongly habit forming (food outside, alcohol, tobacco), others display durability (clothing, small durable items). The authors point out the following implication: Heterogeneity in the composite habit coefficient will emerge, since some people consume a higher share of habit-forming goods than others. Ravina (2007) is the only micro-econometric study that investigates both internal and external habit formation. She uses quarterly US credit card data, which allows to get the household-specific interest (not aggregate interest). As external habit measure, she uses city-level instead of aggregate country data. She finds significant coefficients for the internal (0.29) and external (0.503) habit coefficient. Using monthly data from the Japanese Household Panel Data (JPSC) Iwamoto (2011) finds durability, rather than habits. The study covers just female food consumption data and has a very short time dimension.

In a nutshell, micro-econometric studies provide inconclusive results on habit formation in consumption. Moreover, most papers that support habit formation consider only narrow sub-categories of consumption (food, services, tobacco). This provides little insight into composite consumption preferences.

B.2 Tables

Table B.1: Robustness – Gender Splitting

	(1)	(2)
Dependent Var: $\Delta c(t)$	male	female
$\Delta c(t-1)$; internal	0.0923***	0.0713***
	(0.0242)	(0.0217)
$\Delta \bar{c}(t)$; external	0.1985***	0.2828***
	(0.0277)	(0.0268)
Control variables	Yes	Yes
Time dummies	Yes	Yes
Number of observations	19032	27941
Number of households	1042	1569
Wald-test	359.90	450.55
P-value Wald-test	0.000	0.000
P-value Hansen-test	0.710	0.120
P-value AB(3)-test	0.485	0.992

FOD-GMM (forward orthogonal deviation), two-step.

Windmeijer-corrected standard errors.

Instruments: 2nd and 3rd lag of $\Delta c(t-1)$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Robustness – Including Higher Order Terms

	(1)	(2)	(3)
Dependent Var: $\Delta c(t)$	internal squared	external squared	both squared
$\Delta c(t-1)$; internal	0.0824***	0.0925***	0.0823***
	(0.0172)	(0.0163)	(0.0172)
$\Delta \bar{c}(t)$; external	0.2485***	0.2688***	0.2492***
	(0.0196)	(0.0202)	(0.0197)
internal squared	0.0442		0.0442
	(0.0491)		(0.0490)
external squared		-0.0567	-0.0582
		(0.0454)	(0.0470)
Control variables	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Number of observations	46973	46973	46973
Number of households	2607	2607	2607
Wald-test	726.73	729.28	727.64
P-value Wald-test	0.000	0.000	0.000
P-value Hansen-test	0.194	0.209	0.194
P-value AB(3)-test	0.634	0.741	0.634

FOD-GMM (forward orthogonal deviation), two-step, Windmeijer-corrected standard errors.

Instruments: 2nd and 3rd lag of $\Delta c(t-1)$ and $\Delta c(t-1)^2$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Robustness – Income Growth and Squared Income Growth as Controls

	(1)	(2)	(3)
Dependent Var: $\Delta c(t)$	not instrumented	instrumented	instrumented
$\Delta c(t-1)$; internal	0.1066***	0.0925***	0.0765***
	(0.0199)	(0.0199)	(0.0195)
$\Delta \bar{c}(t)$; external	0.2501***	0.2476***	0.2336***
	(0.0245)	(0.0249)	(0.0254)
Δ income(t)	0.0281***	0.0235***	0.0314***
	(0.0040)	(0.0059)	(0.0068)
Δ income-squared(t)			-0.0026**
			(0.0011)
Control variables	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Number of observations	26283	26283	26283
Number of households	1805	1805	1805
Wald-test	516.65	464.02	449.94
P-value Wald-test	0.000	0.000	0.000
P-value Hansen-test	0.630	0.597	0.570
P-value AB(3)-test	0.885	0.821	0.740

FOD-GMM (forward orthogonal deviation), two-step, Windmeijer-corrected standard errors.

Instruments column 1: 2nd and 3rd lag of $\Delta c(t-1)$, income assumed exogenous.

Instruments column 2: 2nd and 3rd lag of $\Delta c(t-1)$ and Δ income(t).

Instruments column 3: 2nd and 3rd lag of $\Delta c(t-1)$, Δ income(t), and Δ income^2(t).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C

Fourth Chapter

C.1 Further Information

The German Pension System: A Short Overview The German pension system builds on three pillars. The first is the public pension provision, the second the complementary pension provision (operational provisions and additional provisions for functionaries), and the third consists of private pensions. Empirically, the pillars cover 89 percent, 5 percent, and 6 percent of the total pension benefits, respectively. The *Riester-Rent* and the *Rürup-Rent*, which can be assigned to private pensions, are unique elements of the German pension system. The *Riester-Rent* is a privately financed rent, promoted by the government through bonuses. It is primarily directed at low-income individuals. The contributions into the *Riester* account amounts to 4 percent of the before-tax income. The government subsidizes the *Riester* account with 154 Euro for the insured person, and 300 Euro for each child of the insured person. A guaranteed interest rate is provided. The *Rürup-Rent* is primarily directed at self-employed and high-income individuals. Participation is incentivized through the tax-deductibility of the contributions. The annual contribution is voluntary and subject to personal choice, up to a maximum of 20,000 Euro per year. Withdrawals are impossible before reaching retirement. The pension benefits are paid as a monthly rent as long as the agent is alive. On the one hand, both rents (*Riester* and *Rürup*) already reach a substantially amount of German population, and are attractive to different income groups. On the other hand, low transparency and high administrative costs are problematic and demand for improvements.

The subsequent numbers illustrate the non-sustainability of the public pension system. According to Deutsche Rentenversicherung Bund (2010), the expenditures amount to 245.83 billion Euro, but only 181.33 billion Euro were collected through regular contributions. The remaining 64.5 billion Euro, accounting for 26 percent, was paid by the German government — but not from the budget that is designated for old-age

pensions. As a response to this deficit, and to further increases in life expectancy, a pension reform was proposed in 2007. It elevated the entering age for retirement from 65 to 67 years. Recently, in 2014, the new German government counteracted the earlier reform, allowing full-time retirement with age 63, if people fulfill certain conditions.

The German Public Pension Formula: The Accounting The pension benefits, P, are given by $P = E * Z * R * A$. E denotes total payment points (Endgeltpunkte). It is the sum over annual payment points (jährliche Endgeltpunkte), which were collected over working life. Z denotes the access factor (Zugangsfaktor); R represents the type of pension (Rentenart), for instance, old age pension, widow pension, disability pension; and A gives the current pension value (aktueller Rentenwert). The annual payment points are calculated by dividing own income by average income. The value has an upward bound — a so-called contribution ceiling — so that the rich can obtain a maximum value of 2.1. A person with average income gets exactly 1 annual payment point. The access factor, Z, is equal to 1, if a person enters retirement with 65. If a person retires earlier, 0.003 is subtracted for every month. The pension type, R, is equal to one for old-age pensions. The current pension value, A, is revised by the government on a yearly basis. The value is slightly higher in West-Germany than in East-Germany. In the remainder, I use West-German numbers, since a larger fraction of the population lives in West-Germany. The prime example for a person, who earns an average income for the whole life, contributes 45 years (20-65), enters retirement with 65, and receives regular old-age pension, is this: $P = E * Z * R * A = 45 * 1 * 1 * 1 * 26.27 = 1,182.15$ Euro. This value, however, overstates what the *real average* person obtains. This is, because the average person starts contributing later than assumed, is temporarily unemployed throughout working age, and retires earlier than 65. A more realistic computation goes as follows. The average person contributes 40 years, retires with 62.3, and thus, gets an access factor of only 0.904. This results in pension benefits of: $P = 40 * 1 * 0.904 * 1 * 26.27 = 949.92$ Euro. The difference to the prime example is more than 200 Euros. This small calculation exercise illustrates that the *fictive average person calculation* is misleading, and overstates what the *actual average person* can expect from the public pension system.

In practice, the formula is more complex than outlined above. There are, for instance, certain smoothing factors, such as, fictive contribution years for mothers, a correction factor for the East-Germans, and an *accounting subsidy* if the individual wage is very low compared to the average wage in the particular year.

C.2 Tables and Figures

Table C.1: Calculation of the Effective Contribution Rate

Year	Participation Rate	Contribution Rate	Effective Contribution Rate
1991	.907	.180	.163
1992	.904	.177	.160
1993	.898	.175	.157
1994	.893	.192	.171
1995	.891	.186	.166
1996	.893	.192	.171
1997	.889	.203	.180
1998	.875	.203	.178
1999	.896	.197	.176
2000	.895	.193	.173
2001	.895	.191	.171
2002	.896	.191	.171
2003	.894	.195	.174
2004	.876	.195	.171
2005	.879	.195	.171
2006	.881	.195	.172
2007	.882	.199	.176
2008	.886	.199	.176

Source: Statistisches Bundesamt (2010a), Deutsches Institut für Altersvorsorge (2008)

Table C.2: Population, Wage, and Deflator

Year	Population	Annual Gross Wage	Deflator
1991	80274564	21984	75.9
1992	80974632	24036	79.8
1993	81338093	25236	83.3
1994	81538603	26220	85.6
1995	81817499	27372	87.1
1996	82012162	28128	88.3
1997	82057379	28668	90.0
1998	82037011	29364	90.9
1999	82163475	30216	91.4
2000	82259540	30612	92.7
2001	82440309	31404	94.5
2002	82536680	32412	95.9
2003	82531671	33396	96.9
2004	82500849	34152	98.5
2005	82437995	34812	100.0
2006	82314906	35400	101.6
2007	82217837	36276	103.9
2008	82002356	37236	106.6

Source: Statistisches Bundesamt (2010a), Deutsches Institut für Altersvorsorge (2008)

Table C.3: Old-Age Period Value For Different Pension Schemes: Non-Stochastic

income class	income	IPAYG	FF	FF
			risk-free	risky
minimum	9612	298	298	720
1|2	20388	541	638	1630
2|3	28536	695	797	1924
median	32112	762	990	2026
3|4	35988	1098	1242	2125
mean	42528	1490	1559	2274
4|5	47916	1668	1726	2384
2*median	64224	2033	2084	2669
3*median	96336	2537	2587	3117
5*median	160560	3202	3257	3781

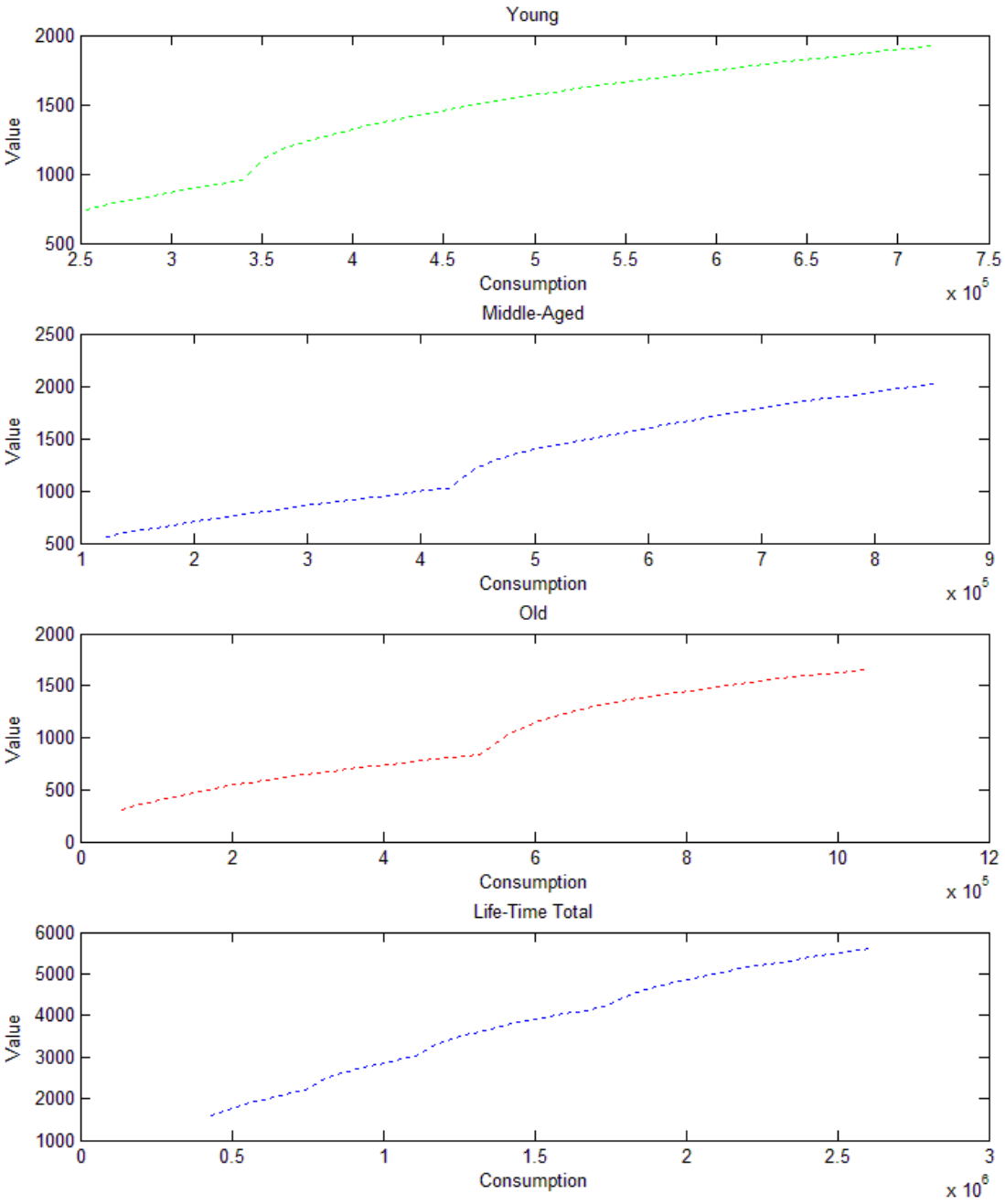
Table C.4: Old-Age Period Value For Different Pension Schemes: Average

income class	income	IPAYG	FF	FF
			risk-free	risky
minimum	9612	300	300	865
1|2	20388	541	638	1468
2|3	28536	695	797	1806
median	32112	762	990	1919
3|4	35988	1024	1242	2117
mean	42528	1465	1551	2335
4|5	47916	1638	1717	2403
2*median	64224	2007	2063	2727
3*median	96336	2501	2556	3151
5*median	160560	3167	3220	3978

Table C.5: Old-Age Period Value For Different Pension Schemes: Minimum

income class	income	IPAYG	FF	FF
			risk-free	risky
minimum	9612	300	300	300
1|2	20388	541	638	473
2|3	28536	695	797	566
median	32112	750	990	606
3|4	35988	804	1241	636
mean	42528	1133	1438	692
4|5	47916	1335	1556	838
2*median	64224	1611	1811	1188
3*median	96336	1966	2167	1656
5*median	160560	2433	2646	2309

Figure C.1: The Shape of the Value Function



Appendix D

Copyright Declaration

Copyright Declaration

I declare that this dissertation and the accompanying computer code have been composed by myself, unless otherwise acknowledged in the text. All verbatim extracts have been distinguished by quotation marks, and all sources of information have been specifically acknowledged. None of the three chapters has been accepted as part of another degree.

Urheberrechtserklärung

Hiermit erkläre ich, dass diese Dissertation und der darin verwendete Computercode von mir verfasst wurden, insoweit nicht anderweitig im Text kenntlich gemacht. Alle wörtlichen Zitierungen wurden durch Anführungszeichen deutlich gemacht. Quellen, welche nicht wörtlich zitiert werden, sondern lediglich Ideen anderer Autoren widerspiegeln, wurden den in den Wirtschaftswissenschaften gängigen Zitierregeln gemäß gehandhabt. Die drei Kapitel wurden nicht im Zusammenhang mit dem Erwerb eines anderen akademischen Abschlusses verwendet.

Appendix E

Summary: English and German Abstracts

Abstract (1) – English

This paper looks at the association of specific consumption goods with subjective well-being (SWB), using a representative sample of US individuals. There is a vast economic literature on the relationship between income and SWB, but surprisingly very little on how individuals spend their income and the associated effects on SWB. Different consumption goods allow to test whether, and through which channels, income might affect SWB. I use panel methods to account for individual heterogeneity. Ordered choice models are used to address the ordinal nature of the SWB data. Unlike linear regression models, this avoids nonsensical out-of-bound predictions and improves efficiency. Total consumption is significantly associated with SWB, but only via certain consumption goods. Consumption is associated with SWB mainly through experiential and conspicuous expenses. Evidence for a causal effect of consumption on SWB is provided.

Abstract (1) – Deutsch

Diese Studie untersucht den Zusammenhang zwischen verschiedenen Konsumgütern und subjektivem Wohlbefinden. Dazu wird ein repräsentativer Datensatz von US-amerikanischen Personen verwendet. Es existiert eine große Anzahl von Studien, welche die Beziehung zwischen Einkommen und subjektivem Wohlbefinden untersuchen. Allerdings gibt es nur unzureichend Forschung darüber, wie Personen ihr Einkommen auf verschiedene Konsumgüter verteilen und die sich daraus ergebenen Effekte auf das Wohlbefinden. Verschiedene Konsumgüter erlauben es zu testen, ob und durch welche Kanäle, Einkommen das Wohlbefinden beeinflusst. Es werden Paneldaten-Methoden verwendet um der nicht-

beobachtbaren Heterogenität von Personen Rechnung zu tragen. Außerdem werden geordnete Entscheidungsmodelle (ordered choice models) verwendet, um die ordinalen Eigenschaften der abhängigen Variable besser zu adressieren. Im Gegensatz zu linearen Regressionsmodellen vermeidet dies Schätzungsvorhersagen außerhalb des eigentlich möglichen Bereichs und verbessert die Effizienz der Schätzungen. Der Gesamtkonsum einer Person steht in positivem Zusammenhang zu ihrem Wohlbefinden, aber lediglich einige Konsumgüter tragen dazu bei. Dies sind vorrangig nicht-materielle Konsumausgaben, sowie Konsumausgaben welche für Andere sichtbar sind und Status signalisieren. Schließlich wird der Nachweis erbracht, dass die Ergebnisse nicht nur eine Korrelation widerspiegeln, sondern tatsächlich einen kausalen Effekt von Konsum auf das subjektive Wohlbefinden aufzeigen.

Abstract (2) – English

This paper investigates the presence and strength of internal and external habit formation in consumption, using monthly household data. The habit hypothesis is used to explain empirical regularities in macroeconomics and finance. Empirical studies based on aggregate data (macro-evidence) leave the micro-behavior unexplored. The micro-evidence is inconclusive and primarily based on food consumption data. But, food consumption is a bad proxy for total consumption — mainly, because food consumption preferences differ considerably from consumption preferences of other goods (Shea (1994)). Thus, I use total household consumption data to test the Euler equations of an additive habit formation model. There is evidence for internal and external habits; the external habit effect is about three times larger than the internal effect. Extensions to alternative habit coefficients are provided.

Abstract (2) – Deutsch

Diese Studie untersucht das Vorhandensein und die Stärke von internen und externen Konsumgewohnheiten. Dazu werden monatsbasierte Haushaltsdaten verwendet. Die Hypothese zur Bildung von Konsumgewohnheiten wird verwendet um empirische Regularien in der Makroökonomie und an den Finanzmärkten zu erklären. Empirische Studien die auf aggregierten Daten basieren (makroökonomische Perspektive) lassen die mikroökonomischen Entscheidungen weitgehend unerklärt. Mikro-ökonometrische Studien zeigen kein einheitliches Ergebnis zur Fragestellung der Bildung von Konsumgewohnheiten. Hinzu kommt, dass sich die Ergebnisse fast ausschließlich auf Konsumdaten zur Ernährung stützen. Allerdings sind Ernährungs-Konsumdaten eine schlechte Näherungsvariable für

die gesamten Konsumausgaben eines Haushalts — hauptsächlich, weil sich die Präferenzen für Ernährungs-Konsumausgaben stark von den Präferenzen für andere Konsumgüter unterscheiden (Shea (1994)). Aus diesem Grund werden in dieser Studie die gesamten Konsumausgaben eines Haushalts verwendet, um die Euler-Gleichungen eines additiven Models zur Konsumgewohnheitsbildung zu untersuchen. Die empirische Auswertung deutet auf interne und externe Konsumgewohnheiten hin, wobei der externe Effekt mehr als dreimal so stark ausfällt wie der interne Effekt. Schließlich werden Erweiterungen zu alternativen Konsumgewohnheitspräferenzen und empirische Schätzungen zu deren Koeffizienten vorgestellt.

Abstract (3) – English

This paper uses a behavioral life-cycle model to analyze different pension schemes when people display non-standard consumption preferences and income-heterogeneity. Retirement resources depend on public pension benefits and individual savings accumulated over working life. Individual savings crucially depend on the choice between low-risk and high-risk assets, because there is a sizable return gap. Mainstream economic models do not adequately capture people's life-cycle asset allocation patterns, that is, their investment in safe and risky assets. The proposed model makes a better prediction. I investigate whether a transition towards a funded pension scheme is desirable, and whether different income classes could benefit from different pension schemes. The rationale is that a non-funded pension component provides better downward risk protection for the low-income earners, whereas a funded pension component is more appealing to rent-seeking, high-income earners. Simulation results reveal that a funded pension scheme is most promising for all income classes — considering reasonable demographic and financial market projections for Germany.

Abstract (3) – Deutsch

Diese Studie verwendet ein verhaltensökonomisches Lebenszyklus-Modell um verschiedene Rentensysteme zu analysieren. Die handelnden ökonomischen Akteure besitzen Präferenzen die sich von den Standardannahmen der Volkswirtschaftslehre unterscheiden. Weiterhin erlaubt das Modell Einkommensunterschiede zwischen den handelnden Personen und beschränkt sich nicht auf die Analyse des Durchschnittsverdieners. Die verfügbaren wirtschaftlichen Ressourcen im Rentenalter hängen von den staatlichen Renten sowie von den privaten Ersparnissen ab, welche über die Lebenszeit angehäuft wurden. Dabei ist die Höhe der privaten Ersparnisse entscheidend davon abhängig, ob Perso-

nen in risikoarme oder risikoreiche Wertpapiere investieren, da gewaltige Ertragsunterschiede zwischen diesen Investmentklassen vorherrschen. Ökonomische Standardmodelle beschreiben diese Investmentaufteilung — über den Lebenszyklus hinweg — nur unzureichend. Das vorgeschlagene Modell hingegen, liefert eine bessere Beschreibung der Aufteilung in die mit verschiedenem Risiko behafteten Wertpapiere. Es wird analysiert, ob ein Übergang zu einem kapitalgedeckten Rentensystem vorzugswürdig ist und ob diese Vorzugswürdigkeit für verschiedene Einkommensklassen gar unterschiedlich ausfällt. Ein möglicher Grund wäre, dass ein umlagefinanziertes Rentensystem Geringverdienern einen besseren Risikoschutz gewährt, wohingegen Besserverdiener eher vom höheren, erwarteten Ertrag des kapitalgedeckten Rentensystems profitieren. Die Ergebnisse zeigen, dass ein Kapitaldeckungssystem für alle Einkommensklassen vorzugswürdig ist, wobei vernünftige Annahmen über den demografischen Wandel und zu erwartende Finanzmarkterträge getroffen werden.

Appendix F

Curriculum Vitae

STEFAN ZIMMERMANN

EDUCATION

10/2010 – present **University of Vienna, Vienna, Austria**

- PhD-Student in Economics. *Research on consumption choice, well-being, and pension design* (empirical and theoretical). Coursework included: academic writing, competition, innovation, econometric methods (panel data, linear/non-linear time series, forecasting, and seasonality), evolutionary games, wage dispersion, Nobel Prize papers, and research seminars.

08/2011 **Aarhus University, Aarhus, Denmark**

- PhD-Summer School: Dynamic Asset Allocation

08/2009-09/2010 **Tilburg University, Tilburg, Netherlands**

- MSc in Economics (*with honors*). Coursework included: behavioral economics, public economics, environmental economics, growth, development, advanced game theory, and competitiveness of the European Union.

10/2006-08/2009 **Humboldt University, Berlin, Germany**

- BSc in Economics (major), Business Administration (minor). Coursework included: macroeconomics, microeconomics, mathematics, statistics, econometrics, finance, international finance, international management, trade, marketing, accounting, computer science, and law.

08/1999-06/2006 **Janusz-Korczak Gymnasium, Finsterwalde, Germany**

- secondary school, A-Level (Abitur), specialized courses: English, biology

08/1993-07/1999 **Janusz-Korczak Grundschule, Finsterwalde, Germany**

- primary school

RESEARCH

Research Interests

Consumer Behavior, Micro-Econometrics, Applied Economics, Behavioral Economics, Happiness Economics, Public Economics

Research Papers

Zimmermann, Stefan (2010), "Hyperbolic Discounting and Pension Design: The Case of Germany", *Netspar Thesis*
The Pursuit of Subjective Well-Being through Specific Consumption Choice
Relative Consumption: The Strength of Internal and External Habits
Life-Cycle Consumption, Asset Allocation, and Pension Design under Non-Standard Preferences
Hyperbolic Discounting and Pension Design: The Case of Germany – Master Thesis
Fiscal Policy and the Multiplier Effect: Some Recent Debates – Bachelor Thesis

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WORK EXPERIENCE

2011-2014 **Insurance (Part-Time)**

- R+V Versicherung, Finsterwalde, Germany
- Data handling, customer service, administration.

2007 **Chartered Accountancy Intern**

- WSC Wirtschafts-und Steuerberatungsgesellschaft mbH, Cottbus, Germany

- Excel-calculations, concerning tax rules for special occupational groups. Digital archiving of customer data and office organization.

2007 **Management Consultancy Intern**

- Unternehmensberatung Konschake & Partner GmbH, Finsterwalde, Germany
- Identification of operational problems, implementation of technological upgrades. Support customers creating a new business, or guidance on entrepreneurial decisions.

Other

- Tief-und Wasserbau GmbH, Doberlug-Kirchhain, intern, 2004
- Kaupisch ITC-Solutions, Finsterwalde, intern, 2002

SKILLS & COMPETENCIES

- **Computer/Software:** Matlab, Stata, Eviews, LaTeX (TeXnic Center, LyX, BibTeX), MS Office, Mendeley, Citavi, HTML, and *touch-typing.*
- **Languages:** German (native); English (proficient); French, Spanish, Dutch (basic).
- **Other:** *Stock Market Certificate*, driver's license B.