Consumer decisions in insurance markets

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Analyzing demand for long-term care insurance and mental health care

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Colophon

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Cover and desgin by
Annette de Vries

Printed by
Optima Grafische Communicatie

ISBN
978-94-6361-657-7

Consumer Decisions in Insurance Markets

Analyzing demand for long-term care insurance and mental health care

Consumentenkeuzes op verzekeringsmarkten

Analyses van de vraag naar ouderenzorgverzekeringen en geestelijke gezondheidszorg

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
rector magnificus

Prof. dr. A.L. Bredenoord

and in accordance with the decision of the Doctorate Board.

The public defence shall be held on
Thursday, April 28, 2022 at 15.30 hrs

by

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An easy climb is rarely worth the view.

Table of Contents

1

Introduction

1. Introduction

1.1. Introduction

Most decisions are made in the face of risk and uncertainty. After all, outcomes are rarely certain beforehand and information on which decisions are based is often imperfect. Economists have long recognized this and studied insurance markets that offer one of the most natural settings for decisions under risk and uncertainty. Yet, standard economic models that explain demand through fully rational utility maximization, do not always manage to explain observed behavior in real-life insurance markets. Behavioral economic approaches that allow for limited rationality and other deviations from utility maximization promise to offer new insights necessary to understand insurance markets and explain these discrepancies.

This thesis aims to add to the understanding of insurance decisions by examining consumer behavior on two insurance markets for health care services, where limited rationality may be particularly apparent. First, it examines individual decisions to take-up insurance in the market for long-term care insurance. The risk of needing long-term care is typically insured many years ahead. Consequently, navigating the market for long-term care insurance requires amongst others apt foresight and the ability to perform advanced calculations. Second, it examines the impact of (a reduction of) insurance coverage on individual decisions to take-up mental health care. Particularly in the domain of mental health care, the question is whether individuals can make fully rational and informed decisions about paying for care.

The remainder of this chapter provides a brief overview of the research on insurance decisions. Section 1.2 explains why one should be interested in studying insurance demand. It continues with an introduction of economic theory on insurance decisions and (Section 1.3.1) and an overview of the related empirical findings (Section 1.3.2). Section 1.4 introduces how behavioral economics may help explain insurance decisions. Finally, Section 1.5 provides an overview of the remainder of this thesis.

1.2. Relevance

Insurance is pivotal in financing health care services. It spreads financial risks by trading them for certain insurance premiums and can thus provide access to care that would otherwise be unaffordable. In addition, insuring frees up precautionary savings that in turn can be spend or invested. Yet, insurance markets are not fully understood. Perhaps one of the biggest puzzles in insurance economics concerns long-term care insurance. In countries where public insurance is incomplete, prolonged nursing home stays are among the largest financial risks faced by the elderly. In the US, for example, these costs can amount to about $100,000 per year. Moreover, the individual variation in both the need and costs of long-term care are high. Consequently, standard economic models predict that there should be substantial demand for long-term care insurance. Observed insurance holding, however, is falling far behind these projections meaning that access to health care and risk protection is not widely obtained.

In addition to these insurance puzzles, well-known market imperfections also threaten the realization of welfare gains in insurance markets. In response, governments across the globe have resorted to regulate insurance markets for healthcare both to promote health and reduce financial risks for their citizens. This has given rise to a great variety in health insurance systems. In some countries, public insurance provides universal coverage for health care and long-term care (e.g., the Netherlands). In other countries, private insurance provides either primary or supplementary coverage against health risks (e.g., the US). A better understanding of insurance markets may aid governments in their regulatory efforts to balance the pros and cons of insurance markets for health care. In particular, it may help better protect individuals against the high costs of care and may benefit those who are currently underinsured.

1.3. Insurance economics

1.3.1. Expected utility theory

Standard economic models hold that demand for insurance is governed by expected utility (EU). A textbook example of an insurance decision under expected utility can be modelled as follows. Consider an individual with initial wealth level W who decides on whether to purchase a single insurance product providing coverage against loss L occurring with probability p.[1] Let's assume that the premium π is actuarially fair (i.e., $\pi = pL$). This individual seeks to maximize a strictly increasing utility function $U(\cdot)$ and to that end compares utility with insurance $U(W - \pi)$ to utility without insurance $pU(W - L)+(1 - p)U(W)$. Because the expected value of both options is the same (i.e., $W - \pi = p(W - L)+(1 - p)W$), the option that maximizes utility is determined by the risk preferences reflected in the utility function.[2] As such, a risk neutral individual, whose utility function mirrors the expected values, has no preference for either option. It is typically assumed, however, that people are risk averse. For risk averse individuals, the certainty provided by an actuarially fair insurance premium maximizes utility.

In practice, this highly stylized version of insurance decisions does not reflect real life insurance decisions very well. Consequently, a broad literature in insurance economics has emerged to obtain predictions of insurance demand in more realistic settings. For example, Arrow (1963) and Mossin (1968) have shown that when there is a loading fee on top of the actuarially fair premium it is optimal to hold full insurance coverage above a deductible. Ehrlich and Becker (1972) have shown how insurance products relate to two other methods of risk management: self-insurance and self-protection (i.e., prevention). Again, others have placed insurance decisions in a broader context of risk portfolios where individuals face multiple, potentially correlated risks (Mayers & Smith 1983).

The stylized model above deviates in another way from insurance practice. It implicitly assumes that consumers and insurers hold symmetric information about risk p (and loss L). In practice this is typically not the case. Consumers may know whether they belong to a good (low) or bad (high) risk group. If insurers do not observe such risk groups, be it directly or indirectly, they cannot account for these risk differences in insurance premiums. This may *generate adverse* selection. After all, with $p^g < p < p^b$ an insurance premium based on p is a much better proposition for bad risks (with loss probability p^b) than for good risks (with loss probability p^g). Therefore, good risks will try to separate from high risks by buying different insurance products with lower coverage and premiums of the old product will rise to reflect p^b rather than p. As the two risk groups themselves again consist of subgroups with different risks, this may even trigger a spiral of selection that continues to segregate good risks from bad ones. Rothschild and Stiglitz (1976) show that consequently an insurance market may not result in a stable equilibrium where insurance can be traded.[3] Even if the market does not (completely) unravel, the outcome is suboptimal. Good risks may pay less, but also obtain less insurance coverage than they would have on a market with symmetric information resulting in a welfare loss. Bad risks have to pay more to obtain the same full insurance coverage and may not be able to afford this, resulting in access problems (Nyman 1999).

Asymmetric information can hamper the efficient functioning of insurance markets in yet another way. After all, loss L and risk p are not static but can be influenced by individuals after obtaining insurance. Yet, insurers are unable to completely monitor individual actions that impact the size and likelihood of insured losses after issuing insurance. Because insurance partially covers these losses, the incentive for insureds to reduce the size or likelihood of losses occurring is reduced, or even absent in the case of full insurance (Arrow 1963; Pauly 1968). Consequently, insurance claims are higher than when insureds behave as if they are uninsured, resulting in higher than optimal premiums. This is called

1 For ease of exposition, I describe full insurance products that cover the entire loss L. Partial insurance products only pay out a proportion of suffered losses.
2 Note that under non-expected utility models, risk-preferences cannot be inferred from the utility function.
3 More lenient assumptions have subsequently been proposed under which equilibria can arise (e.g., Wilson 1977).

moral hazard.[4] Because of moral hazard, the optimal insurance product is in-fact a trade-off between two competing goals: reducing risks and retaining appropriate incentives for efficiency (Zeckhauser 1970).

1.3.2. Empirical findings on (health) insurance decisions

Economists have subsequently set out to empirically examine insurance decisions. As such, some have found that risk preferences indeed explain (some) variation in insurance holding (e.g., Einav, Finkelstein, Pascu & Cullen 2012; Jaspersen, Ragin & Sydnor 2021). Others have looked at correlations of other characteristics with insurance holding. For example, Outreville (2014) provides a literature study on background characteristics that may explain life insurance holding. Studies into the distribution of health insurance over different populations are particularly ubiquitous (e.g., Marquis & Long 1995; Bolhaar, Lindeboom & van der Klaauw 2012; Saltzman 2019). Most studies, however, have focused on analyzing adverse selection and moral hazard. Below we describe their principal findings.

Selection in insurance markets is typically analyzed through estimating the correlation between insurance holding and risk conditional on all underwriting criteria used by insurers when issuing insurance.[5] In addition to controlling for underwriting criteria, this type of analysis requires substantive controls for moral hazard, which may also drive such correlations. Although it is no easy feat to get access both to these underwriting criteria and to individual level data on insurance coverage, insurance claims and underwriting data, there is a substantial number of studies that have done exactly that for different insurance markets.[6] These studies find no clear evidence of adverse selection. However, there is evidence of adverse selection on markets where insurers employ few underwriting characteristics, such as the annuity market in the UK (Finkelstein & Poterba 2002; Finkelstein & Poterba 2004). Results are typically mixed for markets with more substantial pricing and selection mechanisms, such as the US market for life insurance (Cawley & Philipson 1999; He 2009). In the markets for health and long-term care insurance, there is no robust indication for adverse selection either (Cutler & Reber 1998; Cardon & Hendel 2001). An explanation may be that it is offset by advantageous selection, where those who hold more insurance coverage are also more cautious (De Meza & Webb 2001). Evidence of such advantageous selection has been found on the US markets for long-term care (Finkelstein & McGarry 2006) and health insurance (Fang, Keane & Silverman 2008).

The RAND Health Insurance Experiment (HIE) has led the way in studying moral hazard in health care. In the RAND HIE, participants were randomly assigned to different health insurance plans. This enabled an analysis of price sensitivity of health care demand unaffected by selection. Results showed substantially higher health care expenses when coverage was greater and thus provided substantial evidence of moral hazard (Manning et al. 1986). Moreover, the RAND HIE found substantial differences between health care services, with the greatest price response among mental healthcare (Keeler et al. 1988). Afterwards, an extensive literature developed to analyze moral hazard through quasi-experimental methods in different settings and different population. Such studies have generally found similar results.[7] In long-term care, moral hazard seems restricted to home care, because moving to a nursing home is viewed unfavorably by most consumers (Grabowski & Gruber 2007; Konetzka, He, Dong & Nyman 2019).

1.4. Behavioral insurance economics

Some insurance decisions cannot be explained within the standard expected utility framework described above. The observation that people typically choose low deductible plans posits such a puzzle. After all, the preference for low deductibles for modest stakes implies improbably strong risk aversion when fit in the standard expected utility model.

4 It is common to distinguish between two types of moral hazard. Ex ante moral hazard refers to actions that occur before the materialization of a risk but may affect its likelihood or the size of the associated loss. For example, insurance coverage may reduce incentives to take preventive measures. Ex post moral hazard refers to actions that impact the size of the loss after an insured event has occurred.

5 In addition to estimating the regression coefficient of coverage on risk, one may indirectly test for selection through the correlation of the error terms of two jointly estimated models for insurance claims and coverage (Chiappori & Salanié 2000).

6 See Cohen and Siegelman (2010) for a literature review on studies on adverse selection up until 2010

7 See Kiil and Houlberg (2014) for an extensive review of the literature from 1990 till 2011.

Behavioral economics offers new ways to understand such puzzles. Whereas expected utility theory assumes that individuals are fully rational utility maximizers, behavioral economics relaxes this assumption and allows for decision makers with nonstandard preferences or limited rationality that deviate from expected utility. For example, decision makers typically weigh probabilities and tend to be averse to losses, both of which may explain preferences for low deductible plans (Sydnor 2010).

Probability weighting and loss aversion are the cornerstones of perhaps the most well-known behavioral economic model: (cumulative) prospect theory (Tversky & Kahneman 1992). Yet, the umbrella of behavioral economics is much broader. In fact, it is often used to describe all economic models that do not (entirely) comply with expected utility theory. Below, I describe two behavioral economic concepts that may be especially relevant for the understanding consumer decisions in insurance markets: limited rationality and ambiguity.

First, insurance decisions are normally not made under complete rationality. There is widespread evidence of different biases that impact decisions, such as tendencies to adhere to the status quo (Samuelson & Zeckhauser 1988) or to overreact to salient events (Tversky & Kahneman 1974). The impact of such limited rational behavior may be heterogeneous because people have different decision-making abilities (Lusardi & Mitchell 2014; Handel, Kolstad, Minten & Spinnewijn 2020). Insurance decisions are particularly prone to such deviations from rationality because they are complex. After all, insurance decisions require advanced calculations and anticipating the (far) future. Moreover, health and long-term care insurance decisions also require difficult trade-offs between health and wealth.

Second, decisions are often not made with known probabilities, but in the face of ambiguity. Already for a long time, economists have recognized the importance of distinguishing between decisions under risk, with known probabilities, and decisions under ambiguity (or uncertainty), with unknown probabilities (Knight 1921). Even so, the first models of decisions under ambiguity were generalizations of models with known probabilities (Savage 1954). Ellsberg (1961) showed that such generalizations failed to capture the differential attitudes that individuals have towards uncertainty. This has given rise to a growing field of research that analyzes decision-making under ambiguity. The impact of ambiguity may be particularly large in the context of insurance decisions, because both the probability of insured events and the probability of claim reimbursement are ambiguous.

1.5. This thesis

This thesis continues with five research chapters that analyze differences in insurance decisions, assess the information that individuals possess to make insurance decisions and evaluate the impact of ambiguity on insurance decisions. These chapters are primarily written for publication in different economic journals and can be read independently. This also implies that these chapters to some extent overlap in content and differ in structure. The research chapters are followed by a concluding final chapter that binds together the different findings and provides policy recommendations. The subjects of the five research chapters are briefly summarized below.

1.5.1. Insurance puzzles: long-term care insurance and life annuities

Chapter 2 discusses two puzzles of underinsurance: of long-term care insurance – which served as the primary inspiration for this thesis – and of life annuities. It presents the current standing of the theoretical and empirical literature and integrates these findings. The chapter shows that the take-out of long-term care insurance and life annuities is hindered by four comparable mechanisms. First, public insurance substitutes for these products. Second, these markets suffer from adverse selection. Third, preferences deviate from standard expected utility models. Fourth, the products are often misunderstood.

1.5.2. Predicting lifetime nursing home use

Chapter 3 sheds light on the possibilities of adverse selection on the market for long-term care insurance by examining individual's ability to predict lifetime risks of nursing home use. To date research on long-term care insurance has primarily considered adverse selection over relatively short follow-up periods only because of data limitations. This chapter tackles these limitations and shows that subjective lifetime probabilities are also predictive of nursing home use. Moreover, information that is unknown to insurers, remains predictive of survival and beliefs up to 20 years later, indicating that subjective lifetime probabilities may generate adverse selection.

1.5.3. Ambiguous nonperformance risks

Chapter 4 examines the role of nonstandard preferences in insurance decisions. Insurance typically has some unknown probability of not paying out valid claims (i.e., a nonperformance risk). A well-known finding is that individuals have a strong dislike of insurance products that have a known probability of not paying out. This dislike cannot be explained with realistic utility functions (Wakker, Thaler & Tversky 1997. This chapter compares insurance demand for products with known and – more realistic – unknown nonperformance probabilities in a lab experiment. Results show that demand is even lower when the nonperformance risk is ambiguous. Yet, this cannot be explained by a simple measure of ambiguity aversion.

1.5.4. Decision-making abilities and selection in long-term care insurance

Chapter 5 examines differences in decision-making abilities in long-term care insurance. The long-term care insurance market may be particularly difficult to navigate, leading to differences in insurance holding by ability. This chapter shows that decision-making abilities are also correlated with long-term care use and thus generate selection on this market. Furthermore, it is shown that decision-making abilities may reinforce adverse selection from private information: those with greater decision-making abilities are more likely to hold insurance when they have private information of being a bad risk.

1.5.5. Insurance coverage and demand for mental health care

Chapter 6 evaluates the impact of the introduction of copayments in mental health care in the Netherlands. Such schemes are common to counter moral hazard, yet most evidence on their effects are from the US. Moreover, copayments may hit demand for mental healthcare particularly hard as individuals are even more likely to deviate from self-interested behavior (Frank & McGuire 2000). We employ the introduction of a new copayment scheme in 2012 to analyze the price sensitivity of the demand for mental health care in a setting with universal and comprehensive coverage. We find that this copayment scheme substantially decreased mental health care utilization. This decrease was concentrated among treatments with short durations. In addition, we find some heterogeneity in demand responses to the new copayment scheme by gender, but not by socioeconomic status.

2

Insurance puzzles

long-term care insurance and life annuities

With aging populations, the role of private insurance in financing late-in-life risks is likely to grow. Yet, demand for long-term care insurance (LTCI) and life annuities (hereafter annuities) is very limited and lags behind economic projections. This systematic literature review surveys the large number of theoretical and empirical studies analyzing this contradiction. We examine the LTCI and annuity puzzles separately and show which factors limit demand for insurance against both late-in-life risks. Our systematic search rendered 3,945 unique hits and findings of 187 studies were integrated in our analyses. Results hereof suggest that holding of both insurance products is systematically impeded by substitution by social security, adverse selection, nonstandard preferences and limited rationality due to low financial literacy and risk unawareness. Furthermore, insurance holding is concentrated among wealthier and subjectively healthier individuals. A comprehensive approach addressing all four reasons for low uptake may increase insurance holding most effectively and may particularly empower people with lower socio-economic status to make well-informed decisions.

Based on:
"Displaced, disliked and misunderstood: A systematic review of the reasons for low uptake of long-term care insurance and life annuities"

with Erik Schut
in The Journal of the Economics of Ageing, 17, 100236.

2. Insurance puzzles: long-term care insurance and life annuities

2.1. Introduction

Facing aging populations, many developed countries strive to protect against late-in-life risks through policies that ensure adequate elderly care and retirement income. Yet fiscal affordability of such policies is simultaneously impeded by these demographics. Consequently, the role of public policy in protecting against long-term care (LTC) and longevity risks remains small in countries where government policies have traditionally been limited and is decreasing in countries where extensive public programs are being constricted. Hence, social benefits for LTC and longevity risks often provide a minimalist safety net for the worst-off, while others need to buy private insurance to cover those risks.

Limited coverage of public programs and the considerable individual uncertainty about late-in-life risks provide a strong rationale for buying private insurance. Indeed, a market with limited government intervention offers ample freedom to deploy resources and smooth consumption over one's life-cycle. Individuals can purchase a preferred amount of insurance coverage at a preferred point in time, e.g., when income and assets are high to protect against depleting assets due to late-in-life risks when income is lower. Yet in practice, private insurance against LTC and longevity risks lags behind economic projections. The uptake of long-term care insurance (LTCI) is much lower than predicted by standard economic (expected utility) theory (Pestieau & Ponthière 2012). Similarly, economic theory judges that life annuities (hereafter annuities) should play a larger role in insuring against longevity risks than is observed in the current market (Modigliani 1986).

In response, for both distinct but related markets a broad literature has emerged to explain why such underinsurance exists. This research has analyzed both the supply side of the market, where existing insurance products may suffer from design flaws and the demand-side, where people may fail to adequately purchase these products. We focus on demand-side analyses and group this literature into four explanations. First, people could substitute for private insurance with public insurance or family help (e.g., Brown, Coe & Finkelstein 2007). Second, people could have private information about their LTC and longevity risk that risk-rated insurance premiums do not control for. Then primarily the worst risks adversely select into LTCI and annuities, driving up premiums and lowering demand among better risks (e.g., Sloan & Norton 1997). Third, people could have different preferences than those assumed in expected utility models (e.g., Brown, Goda & McGarry 2012). Fourth, behavior of limited rationality not reflected in expected utility evaluations could impact uptake. For example, when people are not perfectly rational, factors such as financial literacy may impact uptake (e.g., Brown 2007).

To evaluate why uptake of LTCI and annuities is so low our paper provides an overview of all factors impacting LTCI and annuity purchase decisions. To date, the only extensive review in the fast-growing field of literature on LTCI evaluates three major research areas (financing, demand, and insurability) by identifying the most significant paths in a citation network (Eling & Ghavibazoo 2019). By contrast, our review provides a more in-depth analysis of the potential explanations for low uptake of LTCI – including more than twice as many empirical studies on LTCI uptake – while simultaneously providing a similar analysis for low uptake of annuities. Hence, our contribution to the literature is fourfold. First, we provide a systematic review of the literature on demand for LTCI and annuities with quality checks (rather than a structured review). Second, we provide overviews of the theoretical and empirical literature separately and for both fields of study. Third, we move beyond summarizing previous results by employing our descriptive results to unravel the underlying reasons for low uptake. Fourth, we compare the reasons for low uptake in both markets.

This chapter continues as follows. Section 2.2 gives an overview of the main LTCI and annuity markets and products. Section 2.3 describes the state-of-the art methods of our systematic review. Section 2.4 integrates the findings of previous theoretical research. Section 2.5 summarizes the findings of empirical research and uses these to explain why uptake of LTCI and annuities is so low. Section 2.6 discusses to what extent the factors that lead to low uptake for LTCI and annuities overlap. Finally, our conclusion and recommendations follow in Section 2.7.

2.2. Background

The uptake of private LTCI differs greatly between countries, in part because there are large differences between social security schemes. Still, private LTCI markets do not necessarily thrive in countries with less generous social security schemes. In the US, for example, LTCI is the primary risk sharing mechanism for many individuals as Medicaid – the public insurance scheme – only provides a means-tested safety net for the lowest income groups. Nonetheless, the American LTCI market covers just a fraction of the total LTC expenditures (Brown & Finkelstein 2007). In the UK, private LTCI is almost absent, notwithstanding the fact that LTC provided by local authorities is also stringently means-tested.

Private LTCI in France and Germany is generally seen to be more successful (Doty, Nadash & Racco 2015; Rothgang 2010). In these countries, LTCI is marketed as a supplement to (income adjusted) social insurance policies. Supplemental LTCI policies are also available in Israel and Singapore (Swiss Re 2014). The downside is that these are bare-bone policies do not nearly cover the costs of LTC and offer limited relief from pressure on public expenditures. Nonetheless, such meagre policies are viewed to be more marketable. With social security protecting against tail-risks, supplemental policies are both more affordable and less prone to uncertain developments of future LTC costs than more comprehensive insurance products.

Similarly, annuity markets are hardly ever substantial, even in case of more extensive social security settings (Rusconi 2008). Generally, we can distinguish two types of annuity products. First there are immediate annuities, in which annuitants are almost immediately entitled to receive annuity income after paying a lump-sum. Such policies are the predominant form of longevity insurance in e.g., the UK, the US and Australia. Second, there are deferred annuities, in which annuitants pay periodic premiums in advance and will start receiving annuity payments at some point in the future. These policies are the conventional type of longevity insurance in countries such as Germany, Denmark and the Netherlands. The main difference between both types is that, in the purchase of immediate annuities, (pension) savings are converted at once to buy an annuity which starts paying out immediately, whereas deferred annuities are purchased through iterative premiums that are converted to future entitlements. Although they differ, neither annuity product is particularly popular in a voluntary setting and when pension savings become available people seem inclined to opt for lump-sum payments rather than annuity payments (Brown, Casey & Mitchell 2007).

To some extent LTCI and annuity markets overlap, because of the availability of combined products. In the US, some products currently offer a LTC rider on top of an immediate annuity. LTC needs can be paid with this annuity and if not all annuity assets are depleted, the remainder will be paid out as death benefits (NAIC 2016). Deferred annuity hybrids are also available, yet less popular. The uptake of these new products seems to outperform that of conventional annuities (NAIC 2016). In Germany, similar products are available, yet their commercial success is unknown (Zhou-Richter & Gründl 2011).

2.3. Methods

We performed a systematic literature review based on state-of-the-art methods (Higgins and Green 2011). Thus, we (1) formulated a protocol with clear research questions and eligibility criteria beforehand; (2) approached an information specialist to develop a highly sensitive search string and search the relevant databases; (3) performed the study selection collaboratively; (4) searched relevant working paper databases manually, snowballed reference lists of all included publications and approached experts to ensure the integrality of the included studies; (5) used a data extraction form that was developed ex ante; (6) graded all included studies based on the strength of their methodology and study design in order to assess the risk of biased results; and (7) integrated the results. Below, we describe this process in-depth.

(1) In the protocol, we laid down the following research questions: (i) which factors impact the uptake of LTCI? and (ii) which factors impact the uptake of life annuities? To be included, publications should:

1. be explicitly about private LTCI, annuities and/or combined life care annuities;
2. focus on uptake and/or demand of these products;
3. identify factors that impact demand;
4. be either empirical or theoretical;
5. when empirical, be on high income countries as defined by the World Bank (2018)
6. when theoretical, be the most recent available applying the specific model;
7. be in English; and
8. be published in a peer-reviewed journal.

(2) A comprehensive search strategy was developed with the help of an information specialist of the Erasmus Medical Center Library. We defined keywords as well as Medical Subject Headings (MeSH) and Embase Subject Headings (Emtree terms) that captured the first two eligibility criteria: a focus on LTCI and/or annuity demand. In order to maximize the identification of potentially relevant publications, we designed the search string to be highly sensitive by including keywords with few (relevant) hits (see Appendix 2.A).

This search string was then used to search a combination of general databases, namely: EMBASE, Medline Ovid, and Web of Science. A general search string was additionally entered in Google Scholar and the first 400 hits were recorded. This combination of database searches was suggested by Bramer, Rethlefsen, Kleijnen and Franco (2017). Following their recommendations we also added the following subject specific databases: CINAHL EBSCOhost (nursing care), PsychINFO Ovid (psychology), ABI inform Proquest (general non-medical) and EconLit (economics). The search was performed on July 3rd 2018 and resulted in 3,945 records to be included in this literature review. A complete overview of the study selection process can be found in Appendix 2.B.

(3) Titles and abstracts of the identified records were stored in EndNote and reviewed simultaneously by both authors following Bramer, Milic and Mast (2017). We scanned the abstracts specifically to identify publications on factors impacting LTCI and annuity uptake decisions as defined in the eligibility criteria. This resulted in the inclusion of 341 publications for full text reading, in which the eligibility criteria from our protocol were applied.

(4) We employed three additional data collection sources to minimize the risk of overlooking potentially relevant publications. First, we manually searched the working-paper series of the NBER, Netspar, Cepar, the Pension Research Council and SHARE from 2006 onwards to identify papers that met eligibility criteria 1 to 7, but which had not yet been published in a peer-reviewed journal. Second, we similarly snowballed reference lists of all articles and working papers included. Third, five experts reflected on the list of included publications and indicated whether any relevant studies were still missing. In this way, we ultimately included a total of 187 studies of which 106 empirical and 81 theoretical.

(5) Relevant data were extracted from the included studies using the predefined data extraction form. This data extraction – which focused on either the most extensive analyses performed or the preferred specification identified by the authors – derived the outcome variable used, the independent variables analyzed, the corresponding associations and whether these were significant at a 5 percent significance level. As our goal is to gain an overview of the directional associations found across different studies – and not to perform a meta-analysis – we do not report strength of association. For empirical studies, we also retrieved the dataset used, the sample size, and the sampling restrictions.

(6) We performed additional quality checks, in order to safeguard the quality of the included studies and incorporate quality aspects in our review. Publications were scored on a scale from A (best) to D (worst) using the relevant measures from the GRADE method (Schünemann et al. 2013). Specifically, an initial grade was based on study design, with quasi-experiments (B) ranking above observational studies (C) and other means of data collection (D). Points were then deducted for study limitations and publication biases. Studies that scored malus points in excess of rank D, were excluded retrospectively. In total, 19 studies have been excluded because of quality issues (see Appendix 2.B). The main reason for exclusion was that studies failed to (properly) apply multivariate analyses and hence reported monocausal results. As such, all studies included contained multivariate analyses.

(7) We combine findings of both theoretical and empirical literature as follows. For theoretical research, we integrate these by describing the main findings on LTCI (Subsection 2.4.1) and annuity uptake (Subsection 2.4.2). This overview is not intended to compare theoretical predictions based on underlying assumptions, but rather to shed light on the different factors impacting insurance uptake that the theoretical literature provides. For empirical research, we employ a vote count to give an overview of the results of included studies (Section 2.5). We pay particular attention to the strongest level of evidence (B) that results from quasi-experimental studies evaluating causal relationships. For both theoretical and empirical papers we distinguish between individual level characteristics (e.g., age, gender and income) and contextual characteristics (e.g., social benefits and taxes) that could impact uptake. After presenting our integrated results, we discuss how the findings can explain low uptake through substitution, adverse selection, insurance preferences and limited rationality for LTCI (Subsection 2.5.1.3) and annuities (Subsection 2.5.2.3). Finally, we show which factors impact uptake of both products in Section 2.6.

2.4. Theoretical literature

2.4.1. Demand for LTCI

Standard insurance theory in its simplest form posits that LTCI is valuable for those who are risk averse (i.e., with a concave utility function). Such a risk averse individual prefers the certainty provided by insurance coverage over the uncertainty of facing an uninsured risk and is willing to pay a premium to attain such certainty. However, uptake of LTCI as predicted by standard insurance theory is much higher than as observed in practice. Hence, researchers have sought to expand and adjust the model to fit actual market conditions better. Here we provide an overview of the main demand-side adaptions of the basic model.

First, people may rely on several substitutes for LTCI. At the individual level, private LTCI can be crowded out by informal care (De Donder & Pestieau 2017). Potentially, LTCI can be crowded out by home equity as well. If home equity is illiquid, individuals may have to sell their house in order to pay for LTC. If reverse mortgages ensure that home equity is more liquid, then individuals could use these assets to purchase LTCI without directly selling their house (Davidoff 2010; Davidoff 2009; Shao et al. 2017). At the contextual level, private LTCI can be crowded out by means-tested public LTCI (Fabel 1996; Pauly 1990). Brown and Finkelstein (2008) predict that this is particularly the case for individuals with lower wealth levels. Friedberg, Sun and Webb (2014) extend these findings.[8] Still, policy interventions that protect against spending down – such as partnership programs – are predicted to barely increase LTCI uptake and to mostly benefit those who would purchase private LTCI anyway (Sun & Webb 2013).

Second, it is argued that individuals with high LTC needs will adversely select into LTCI. For example, if young individuals have a low probability of needing LTC they will prefer to purchase LTCI later to avoid a loss in expected income (Meier 1999). Consequently, only older individuals and those with high LTC risks will purchase LTCI. Even if insurers risk-rate premiums – by for example using age as a proxy of LTC risk – this will not reflect all private information on LTC risks that individuals possess and adverse selection could persist.

Third, individual preferences could deviate from those assumed in the standard bare-bones insurance model based on expected utility theory. For example, it has been suggested – contrary to what is usually assumed – that marginal utility of consumption in a period of LTC needs is lower, than in a period of good health (Finkelstein et al. 2009). If that is the case, then LTCI is less attractive because it shifts consumption from a period with high marginal utility to a period with lower marginal utility (Meier 1998). Furthermore, individuals may underestimate their LTC risk. Such probability underweighting (De Donder & Leroux 2014) may ensure a lower valuation of insurance and decrease LTCI demand.

Additionally, family dynamics are expected to impact LTCI demand. Bequest motives can make LTCI more attractive, as these encourage individuals to protect their wealth (Lockwood 2014). At the same time, buying LTCI can decrease informal caregiving and may therefore be unattractive even in view of bequest motives (e.g., Pauly 1990; Zweifel & Strüwe 1996, 1998). This suggests that if people prefer informal care they may strategically decide not to buy LTCI in order to increase informal caregiving.

2.4.2. Demand for annuities

For annuities, the seminal work of Yaari (1965) shows that an individual who (1) maximizes a time separable utility; (2) faces uncertainty about the timing of death only; and (3) has no bequest motive, should fully annuitize at actuarial fair prices. Subsequent theoretical research has analyzed whether different assumptions could explain why actual uptake is lower. For example, in a well-known extension Davidoff, Brown, and Diamond (2005) show that the results of Yaari (1965) hold under less strict utility assumptions, but do not hold when insurance markets are incomplete. In this theoretical overview, we summarize the main demand-side extensions on Yaari (1965).

First, just as for LTCI, substitution has been highlighted as an explanation for low uptake. At the individual level, multiple studies show that families can rely on various substitutes for formal annuities. Some identify couples as a potential group for whom annuities might be less valuable, because they inherently already pool risks between themselves (Brown & Poterba 2000). Similarly, others show that longevity risks can be pooled efficiently by families (Schmeiser & Post 2005; Stamos 2008). At the contextual level, substitution can also occur: social benefits can crowd out private annuities (Pashchenko 2013; Purcal & Piggott 2008). Moreover, social benefits can particularly deter individuals with shorter life expectancy from entering the annuity market and thus aggravate adverse selection effects (Heijdra et al. 2015; Walliser 2000).

In addition, a broad range of papers has argued that the design of current annuity products is suboptimal, which may encourage substitutional strategies.[9] In addition, Kingston and Thorp (2005) show that – as annuitization is often irreversible – not annuitizing offers

8 This is likely at least partly due to affordability. Ma and Sun (2017) show that cheaper policies that protect only against tail-risks would increase private LTCI coverage among those with lower wealth levels.

9 Part of this research focuses on strategies or products that are either very recent innovations or that do not yet exist in practice and as such do not explain underannuitization. We will therefore suffice by referring the reader to some of this literature. Specifically on: annuity options (Sheshinsky 2010), on products that concentrate on late-life payouts (Scott et al. 2011) and withdrawal rules (e.g., Dus, Maurer & Mitchell 2005; Horneff, Maurer, Mitchell, et al. 2008). Finally, some recent studies analyze optimal combinations of innovative products and withdrawal strategies (e.g., Blanchett 2015; Hanewald, Piggott & Sherris 2013).

valuable flexibility through retention of the option to annuitize later on. Other studies show that annuitization is only valuable from a certain age (or wealth level). Moreover, self-annuitization (e.g., Milevsky 1998; Stabile 2006; Milevsky & Young 2007b) or other investments (Di Giacinto & Vigna 2012) may better protect the liquidity of assets and may be optimal until a certain age (or wealth threshold) and depending on the returns offered by other investments (Hainaut & Devolder 2006). Studies allowing for flexible investment portfolios over time derive qualitatively similar results (Horneff et al. 2008b; Horneff et al. 2008a; Milevsky & Young 2007a).

Second, adverse selection can play a role just as for LTCI; if risk-rated premiums do not reflect private information, only those with the worst risks will purchase annuities. Indeed, it is argued that individuals infer such private information on their longevity risk from their health status (e.g., Gupta & Li 2013). Mitchell, Poterba, Warshawsky and Brown (1999) show that prices are higher due to adverse selection, but with realistic parameters this cannot explain low uptake for estimated loading factors. Balls (2006) draws qualitatively similar conclusions and shows that adverse selection based on health status both decreases the value of annuities on the market and shrinks the market size.

Third, people can have different preferences than those assumed in the Yaari (1965) model. As for LTCI, at the individual level a common extension has been to introduce bequest motives (e.g., Kotlikoff & Spivak 1981). Davidoff, Brown and Diamond (2005) show that under fair premiums it is still optimal to annuitize all wealth, except for the part that one wishes to bequeath. Still, under unfair premiums bequest motives can eliminate demand (Friedman & Warshawsky 1990; Vidal-Meliá & Lejárraga-García 2006, 2004). Bequest motives need not be strong; demand can be eliminated by modest bequest motives (Lockwood 2012) or even by any positive bequest motive if an individual is sufficiently risk averse (Bommier & Grand 2014). As for LTCI, it is also argued that parents may strategically purchase annuities (Bernheim et al. 1985). Specifically, parents may use bequests to influence behavior of their children. For example, they could decrease their bequest (or threaten to) by purchasing nonbequeathable annuities to stimulate their children to give them more attention.

Finally, uncertainty over future health costs may be important. Annuities may be used to hedge against the uncertain costs of health shocks when older (Ai et al. 2017; Pang & Warshawsky 2008). Yet, health risks may also impose liquidity constraints by requiring extra savings or insurance spending at a younger age and limit the assets available for annuitizing (Peijnenburg et al. 2017; Reichling & Smetters 2015). Moreover, if longevity and health costs are negatively correlated – i.e., if a negative health shock leads to higher health costs while decreasing longevity – this provides a hedge for both uncertainties and decreases annuitization (Zhao 2015).

2.5. Empirical literature

2.5.1. Uptake of LTCI

An extensive empirical literature analyzes LTCI uptake in different countries. A descriptive overview of this research and the data analyzed is presented in Table 2.1. A large share of the LTCI literature analyzes one or more of the 12 waves of the US Health and Retirement Study (HRS). Moreover, many studies focus on the 'near elderly' – usually between 50 and 70 years old – who are not in need of care as those individuals should be preparing for later. Of the 62 studies included, most (42) are observational studies without serious limitations (graded C). 5 studies are quasi-experimental (B), and 15 are observational studies that suffer from some limitations or fail to comprehensively describe their methods for data collection (D).

Table 2.1 Overview of included studies on LTCI uptake

Authors	#	Dataset	Country	N	Sample restrictions
Akaichi, Costa-Font and Frank (2020)	1	Survey of Long-term Care Awareness and Planning	US	15,298 ind.	40-70 years old and not institutionalized
Allaire, Brown and Wiener (2016)	2	Survey of Long-term Care Awareness and Planning	US	12,936 ind.	40-70 years old and not institutionalized
Ameriks, Briggs, Caplin, Shapiro and Tonetti (2018)	3	Survey	US	1,086 ind.	over 55 years old with at least $10k in Vanguard accounts
Barnett and Stum (2013)	4	Survey	US	803 ind.	public employees eligible to purchase LTCI
Bergquist, Costa-Font and Swartz (2018) (a)	5	NAIC sales	US	50 states + DC	n.a.
Bernet (2004)	6	HRS (wave 5)	US	16,851 ind.	over 53 years old
Boyer, de Donder, Fluet, Leroux and Michaud (2017)	7	Survey	Canada	2,000 ind.	50-70 years old
Brau and Bruni (2008)	8	Survey	Italy	1,176 ind.	25-70 years old
Brau, Bruni and Pinna (2010)	9	Survey	Italy	1,176 ind.	25-70 years old
Brown, Coe and Finkelstein (2007) (a)	10	HRS (wave 3-5)	US	12,402 ind.	55-69 years old
Brown et al. (2012)	11	American Life Panel	US	1,569 ind.	over 50 years old
Browne and Zhou-Richter (2014)	12	Socio-Economic Panel	Germany	3,749 ind.	over 35 years old and not in need of care
Caro, Porell and Kwan (2011)	13	HRS (wave 6-7)	US	2,747 couples	married couples with partners both over 65 years old
Chatterjee and Fan (2017)	14	HRS (wave 11)	US	21,696 ind.	over 52 years old
Coe, Skira and Van Houtven (2015)	15	HRS (wave 4-8)	US	8,349 ind.	51-61 years old and not institutionalized
Cornell and Grabowski (2018) (a)	16	HRS (wave 3-11)	US	13,285 ind.	50-69 years old
Costa-Font and Font (2009)	17	Survey	Spain	324 ind.	over 18 years old
Costa-Font and Rovira-Forns (2008)	18	Survey	Spain	324 ind.	over 18 years old
Courbage and Roudaut (2008)	19	SHARE (wave 2)	France	2,530 ind.	over 50 years old
Courtemanche and He (2009) (a)	20	HRS (wave 4-7)	US	8,566 ind.	55-65 years old
Cramer and Jensen (2006)	21	HRS (wave 6-7)	US	9,863ind.	over 55 years old and without LTCI
Curry, Robison, Shugrue, Keenan and Kapp (2009)	22	Focus groups and in-depth interviews	US, CT	6 focus groups op 9 and 32 interviews	having a direct experience with LTCI

(continued on next page)

Table 2.1 (continued)

Authors	#	Dataset	Country	N	Sample restrictions
Cutler, Finkelstein and McGarry (2008) (b)	23	AHEAD (wave 2)	US	7,183 ind.	65-90 years old
Doerpinghaus and Gustavson (2002)	24	HIAA, AARP and NAIC sales	US	50 states + DC	n.a.
Finkelstein and McGarry (2006)	25	AHEAD (wave 2)	US	5,072 ind.	over 72 years old
Friedberg, Hou, Sun and Webb (2017)	26	HRS (wave 6-11)	US	891 ind.	over 65 years old and owning LTCI in 2002
Gan, Huang and Mayer (2015)	27	HRS (wave 3-5)	US	5,000 ind.	over 73 years old
Goda (2011) (a)	28	HRS (wave 3-8)	US	15,822 ind.	50-69 years old
Gottlieb and Mitchell (2015)	29	HRS (wave 11)	US	487 ind.	over 50 years old
Gousia (2016)	30	SHARE (wave 5)	Austria, Italy, France, Denmark, Israel and Czech Republic	19,116 ind.	over 50 years old
He and Chou (2020)	31	Survey	Hong Kong	1,613 ind.	over 40 years old
Jiménez-Martín, Labeaga-Azcona and Vilaplana-Prieto (2016)	32	SHARE (wave 1, 2 and 5)	Spain	10,867 obs.	over 50 years old and owning either LTCI or private health insurance
Kennedy, Gimm and Glazier (2016)	33	NHIS	US	14,393 ind.	40-65 years old
Kitajima (1999)	34	Survey	Japan, Tokyo	710 ind.	over 40 years old
Konestzka and Luo (2011)	35	HRS (wave 3-10)	US	3,974 ind.	over 50 years old and reporting LTCI ownership in at least one year
Kumar, Cohen, Bishop and Wallack (1995)	36	Survey	US	10,489 ind.	purchasing LTCI or being approached by an agent
Li and Jensen (2012)	37	HRS (wave 6-9)	US	2,085 ind.	over 50 years old and reporting LTCI ownership in at least one year
Lin and Prince (2013)	38	HRS (wave 6-10)	US	12,695 ind.	over 50 years old
Lin and Prince (2016)	39	HRS (wave 6 -10)	US	12,695 ind.	over 50 years old
Lutzky and Alecxih (1999)	40	Interviews	US	110 ind.	experts, insurance agents, consumer groups and regulators
McCall, Mangle, Bauer and Knickman (1998)	41	Survey	US	1,626 ind.	55-75 years old
McGarry, Temkin-Greener and Li (2014)	42	NHATS (2011)	US	8,245 ind.	over 65 years old
McGarry, Temkin-Greener, Chapman, Grabowski and Li (2016)	43	HRS (wave 10)	US	12,796 ind.	over 50 years old

(continued on next page)

Table 2.1 (continued)

Authors	#	Dataset	Country	N	Sample restrictions
McGarry, Temkin-Greener, Grabowski, Chapman and Li (2018)	44	HRS (wave 10)	US	15,963 ind.	over 50 years old
McNamara and Lee (2004)	45	HRS (wave 3-5)	US	6,220 ind.	over 50 years old and reporting LTCI ownership in at least one year
Mellor (2000)	46	AHEAD (wave 1)	US	8,021 ind.	over 70 years old
Mellor (2001)	47	AHEAD (wave 1) PSD	US	7,775 ind. 1,634 ind.	over 70 years old over 50 years old
Nixon (2014)	48	AHIP sales data	US	50 states + DC	n.a.
Oster, Shoulson, Quaid and Dorsey (2010)	49	PHAROS and HRS (wave 5)	US and Canada	7,356 ind.	26-64 years old
Pincus, Hopewood and Mills (2017)	50	Survey	US	1,305 ind.	30-79 years old
Pinquet, Guillén and Ayuso (2011)	51	Insurance data	Spain	150,123 ind.	n.a.
Schaber and Stum (2007)	52	Survey	US	509 ind.	state employees
Sloan and Norton (1997)	53	AHEAD (wave 1-2) HRS (wave 1-2)	US	5,292 ind. 13,312 ind.	over 70 years old 51-61 years old
Sperber et al. (2017)	54	Focus groups	US	80 ind.	elderly parents and adult children
Stevenson, Frank and Tau (2009)	55	NAIC sales	US	50 states + DC	n.a.
Stum (2008)	56	Survey	US	446 ind.	state employees
Swamy (2004)	57	Survey	US, MD	1,394 ind.	40-70 years old
Tennyson and Yang (2014)	58	CRWB	US, NY	693 ind.	50-72 years old
Unruh, Stevenson, Frank, Cohen and Grabowski (2016)	59	AHIP/LifePlan	US	5,240 ind.	purchasing LTCI or being approached by an agent
Van Houtven, Coe and Konetzka (2015)	60	HRS (wave 3-10)	US	22,742 ind.	over 50 years old
Wu, Bateman, Stevens and Thorp (2017)	61	Survey	Australia	1,008 ind	55-64 years old
Zhou-Richter, Browne and Gründl (2010)	62	Survey	Germany	914 ind.	adult children

Notes: (a) Quasi-experimental study (highest level of evidence available). (b) Also analyzes annuity uptake.

As for the dependent variable of LTCI uptake, different measurements are used throughout the empirical literature. Large longitudinal surveys such as the HRS or the Survey of Health Aging and Retirement in Europe (SHARE) elicit revealed preferences by asking for ownership status which is occasionally used to determine changes in ownership status (both purchasing and lapsing). For example, the HRS asks respondents: "Not including government programs, do you now have any long-term care insurance which specifically covers nursing home care for a year or more or any part of personal or medical care in your home?" Other studies have measure stated preferences, through willingness to pay elicitation, discrete choice experiments (Brau et al. 2010; Brau & Bruni 2008) or referendum-approaches (Costa-Font & Font 2009; Costa-Font & Rovira-Forns 2008). When revealed and stated preference analyses systematically lead to qualitatively different results, we reflect on this in our interpretation. Generally, however, this is not the case.

2.5.1.1. Individual factors

Table 2.2 summarizes the main findings of the empirical studies on individual factors associated with LTCI uptake. We refer to Appendix 2.C for a granular insight into our data, as it shows exactly which studies have found which associations and distinguishes between revealed and stated preferences. Below we reflect on these factors one-by-one.

Table 2.2 Overview of findings by studies on individual factors associated with LTCI uptake

Factor	Association						Total
	Negative		None		Positive		
	#	%	#	%	#	%	#
Demographics							
Female (a)	4	11%	20	54%	13	35%	37
Age	8	22%	18	49%	11	30%	37
Non-white (b)	1	6%	13	81%	2	13%	16
Socio-economic status							
Education	2	7%	10	33%	18	60%	30
Income	0	0%	14	39%	22	61%	36
Home ownership	2	50%	2	50%	0	0%	4
Wealth	1	4%	10	37%	16	59%	27
Family							
Number of children (c, d)	7	33%	13	62%	1	5%	21
Married (d, e)	3	9%	25	78%	4	13%	32
Bequest motive	0	0%	4	57%	3	43%	7
Subjective risk							
Subjective health	2	6%	19	61%	10	32%	31
Subjective LTC risk (f)	0	0%	5	26%	14	74%	19
Subjective longevity	0	0%	6	100%	0	0%	6
Objective risk ADL impairments	1	6%	14	78%	3	17%	18
Preferences							
Risk aversion	2	29%	3	43%	2	29%	7
Formal care preference	0	0%	0	0%	3	100%	3
Trust in insurers	0	0%	0	0%	2	100%	2
Understanding							
Financial literacy	1	20%	0	0%	4	80%	5
System knowledge	0	0%	4	80%	1	20%	5

(continued on next page)

Table 2.2 (continued)

Factor	Association						Total
	Negative		None		Positive		
	#	%	#	%	#	%	#
Cognitive intactness	0	0%	3	75%	1	25%	4
Salience							
Awareness of LTC risks	0	0%	3	38%	5	63%	8
LTC experience (g)	2	11%	9	47%	8	42%	19

Notes: (a) Discrepancy in results of stated and revealed preferences studies. (b) Seven studies report different associations for "black", "Hispanic" and/or "other" and have been counted under "none". (c) Three studies report having children (or not) rather than the number of children. (d) Four studies report household size and have been counted under both children and married. (e) Three studies report different associations for married individuals compared to individuals who are single, divorced, or widowed and have been counted under "none". (f) Two studies reporting different associations for home care and nursing home expectations have been counted under "none". (g) Three studies report different associations for different proxies of LTC experience and have been counted under "none".

Most studies either find that women are more likely to buy or own LTCI (35 percent) or that there are no significant differences in uptake between men and women (54 percent). Notably, there are differences between studies that analyze stated preferences and those that analyze revealed preferences; most hypothetical studies find no association with gender, whereas studies analyzing actual uptake, ownership and lapsing do. This overall positive association matches with the fact that LTCI is of more value for women as they live longer than men and are more likely to outlive their partner. This especially applies since gender-based premium differentiation in insurance products is forbidden in the EU (European Union 2004) and has only recently been introduced for LTCI in the US (Carrns 2014).

The relationship between LTCI uptake and age is less straightforward, with 22 percent of the included studies finding negative associations and 30 percent reporting positive associations. Moreover, these results should be interpreted with caution as they may reflect cohort effects for studies that employ age-cohorts such as the HRS. Some studies additionally incorporate effects of age squared. These generally report a significantly positive (Konetzka & Luo 2011) or negative sign (Bernet 2004; Courbage & Roudaut 2008; Gousia 2016; Mellor 2001, 2000), with only two studies finding no significant squared age effects (Ameriks et al. 2018). This may be indicative of an ambiguous non-linear relationship between age and uptake with the directional impact of age changing around a certain age. However, studies analyzing the impact of reaching the age 65 on LTCI uptake find mixed directional effects (Allaire et al. 2016; Pinquet et al. 2011; Van Houtven et al. 2015).

Many studies also analyze the association of ethnicity with LTCI uptake. Although a dichotomous comparison between white and non-white as reported in Table 2.2 reveals no clear uptake pattern, comparisons with specific ethnicities do. These show that uptake of LTCI is markedly lower amongst Hispanics.[10] At the same time, being black[11] or having another non-white ethnicity[12] does not seem to be associated with LTCI coverage.

Different aspects of socio-economic status seem to be important determinants of LTCI uptake. Specifically, some studies find a positive association of subjective social class (He & Chou 2020) or subjective economic condition (Kitajima 1999) and LTCI uptake. More generally, Table 2.2 shows that a majority of the studies finds a positive association between education, income or wealth and LTCI uptake. Evidence suggests that unaffordability of

10 Of the 10 studies analyzing this, 1 finds a positive association (Kennedy et al. 2016), 5 find a negative association (Caro et al. 2011; Konetzka & Luo 2011; McGarry et al. 2016, 2014; McNamara & Lee 2004), and 4 find no association (Cramer & Jensen 2006; Li & Jensen 2012; McGarry et al. 2018; Stevenson et al. 2009)

11 Of the 12 studies analyzing this, 4 find a positive association (Kennedy et al. 2016; McGarry et al. 2018; Stevenson et al. 2009; Van Houtven et al. 2015), 3 find a negative association (Caro et al. 2011; Konetzka and Luo 2011; Li & Jensen 2012), and 5 find no statistically significant association (Cramer & Jensen 2006; McGarry et al. 2016, 2014; McNamara & Lee 2004; Swamy 2004).

12 Of the 8 studies analyzing this, 2 find a negative association (McGarry et al. 2018, 2016) and 6 find no statistically significant association (Konetzka & Luo 2011; Li & Jensen 2012; McNamara & Lee 2004; Stevenson et al. 2009; Swamy 2004; Van Houtven et al. 2015).

LTCI products may at least partially drive these associations (Brown et al. 2012; Schaber & Stum 2007). Zooming in on income effects, all studies find negative income squared effects (Bernet 2004; McNamara & Lee 2004; Mellor 2001, 2000). Together, these findings suggest that income initially enables purchase of LTCI, but above a certain income level people rely more on self-insurance. For squared wealth, the same association is found by two studies (Bernet 2004; McNamara & Lee 2004), while two other studies find no significant squared effects (Mellor 2001, 2000). Additionally, home ownership is associated with lower uptake (Boyer et al. 2017; Costa-Font & Rovira-Forns 2008; Stevenson et al. 2009; Wu et al. 2017), although studies that analyze the home value in addition to wealth do not find theoretically predicted lower LTCI uptake (McGarry et al. 2018; Mellor 2000; Sloan & Norton 1997).

Family dynamics, which have been extensively debated by theorists, are found to some extent in LTCI practice. Table 2.2 shows that bequest motives are likely associated positively with LTCI uptake.[13] Furthermore, being married does not seem to be systematically associated with LTCI uptake. Having more children may decrease LTCI uptake (33 percent), but the majority of the studies (62 percent) reports no significant association. Analysis of other measures of contact with one's children, such as their vicinity (Kumar et al. 1995; Unruh et al. 2016), co-residence (Coe et al. 2015b; He & Chou 2020) or size of the entire family (Brau & Bruni 2008; Costa-Font & Font 2009; Costa-Font & Rovira-Forns 2008; Schaber & Stum 2007) does not reveal a clear association with LTCI uptake.

In addition, Table 2.2 reveals that the subjective risk of needing LTC is generally positively associated with LTCI demand. In other words, individuals who think they are at higher risk of needing LTC are also more likely to buy LTCI. At the same time, self-rated health seems positively associated with LTCI demand, with one third of the studies finding a positive association and 61 percent finding no significant association. This indicates that healthier individuals may be more likely to buy LTCI. However, these two results are not necessarily contradictory. If people associate longevity with a higher risk of LTC needs, this may prompt the observed pattern; subjectively healthier individuals would expect to live longer and hence expect to have a higher LTC risk (Cramer & Jensen 2006). At the same time, there is no evidence that objective health or subjective longevity is related to demand for LTCI.

Table 2.2 shows that the number of impairments in ADLs is not associated with LTCI uptake, despite the fact that ADL impairments are used for both underwriting and determining benefits eligibility (Cornell et al. 2016). Similarly, other measures of objective health such as the number of hospitalizations in the previous year (Brau & Bruni 2008; Browne & Zhou-Richter 2014), drug usage (Bernet 2004), various existing conditions (e.g., Browne & Zhou-Richter 2014; Gousia 2016) and BMI (Jiménez-Martín et al. 2016), are not systematically associated with uptake.

Interestingly, risk aversion does not seem to be associated with insurance decisions. At the same time, LTCI uptake increases with ownership of health insurance (Brau et al. 2010; Brau & Bruni 2008; Browne & Zhou-Richter 2014; Chatterjee & Fan 2017) and life insurance (Chatterjee & Fan 2017; Jiménez-Martín et al. 2016; McNamara & Lee 2004). Some studies argue that preventive health behaviors or wearing seatbelts may be indicative of risk behavior and show that these are positively associated with LTCI uptake (Finkelstein & McGarry 2006; Gan et al. 2015; Gottlieb & Mitchell 2015; McGarry et al. 2018 2016). However, other risk behaviors (smoking, drinking and exercising) are not found to have an effect on uptake (e.g., Courbage & Roudaut 2008; Gottlieb & Mitchell 2015; Jiménez-Martín, Labeaga-Azcona & Vilaplana-Prieto 2016). Altogether, this suggests that although

13 This relationship is even more clear for bequest expectations, as all studies that analyze bequest expectations find a positive association with LTCI uptake (Courbage & Roudaut 2008; Konetzka & Luo 2011; McGarry et al. 2018, 2016), Yet, this could also be driven by reverse causality.

risk aversion is unrelated with LTCI uptake, real life measures of more general insurance preferences or risk behaviors may be associated with LTCI uptake.

Furthermore, there is evidence that LTCI uptake varies with individual perceptions of the value of LTCI[14] and preferences for LTC. That is, people who dislike informal care are more likely to take out LTCI, as displayed in Table 2.2. People who prefer to stay home to going to a nursing home are less likely to buy LTCI (McCall et al. 1998; Tennyson & Yang 2014). And people who have a negative view of public care may buy more LTCI (Brau & Bruni 2008), although another study finds no significant association (Ameriks et al. 2018). Similarly, people may well prefer freedom offered by private LTCI with voluntary coverage to public insurance with mandatory coverage (Akaichi et al. 2020). In line with this, Sperber et al. (2017) find that LTCI is perceived to support autonomy in arranging LTC and that expectations of future autonomy influence uptake decisions. This may also be reflected in the fact that valuing planning may increase uptake (Unruh et al. 2016), even though other studies find no significant effect (Gousia 2016; He & Chou 2020). Finally, Table 2.2 shows that people who trust their insurer to pay out future claims, are more likely to take out LTCI.

Measures of product understanding seem to be strongly associated with LTCI uptake according to Table 2.2. Financial literacy – measured as knowledge of percentages, compound interest, inflation and/or risk diversification – appears to be positively associated with LTCI demand. Also, having a financial planner (Kumar et al. 1995; McCall et al. 1998)[15] or working in finance (Lin & Prince 2016) seems to be associated with uptake. At the same time, measures of cognitive intactness such as the ability to count backwards or remember the current president are not associated with different levels of uptake, nor is knowledge of the LTC system (e.g., knowledge of nursing home costs (Boyer et al. 2017; Unruh et al. 2016)). Finally, two qualitative studies highlight the importance of access to information on LTC in decision making for LTCI (Curry et al. 2009; Lutzky & Alecxih 1999).

Salience of LTC risks is also important in LTCI uptake. A risk is said to be salient when one has been previously confronted with it and is more aware of the risk because of that experience. Most studies show that various proxies of awareness – such as having discussed LTC, being adequately informed and knowing of LTCI existence – are associated positively with demand. However, it is unclear whether these results imply a causal relationship or show that people who purchase LTCI are simply more aware of LTC risks because of that purchase. An indirect way of analyzing this relationship further, is by looking at LTC experience, e.g., providing informal care to others or having close relatives needing LTC. The available evidence suggests that this may be positively associated with LTCI uptake, as 42 percent of the studies find a positive association and 47 percent find no significant association. Moreover, individuals who have experienced health shocks – whether positive or negative – are more likely to own LTCI (Konetzka & Luo 2011), which may also suggest that awareness of LTC risks increases uptake. In addition, over or underweighting the risk of needing LTC could further impact uptake (Boyer et al. 2017).

2.5.1.2. Contextual factors

At the contextual level, Table 2.3 highlights the importance of both generosity of social benefits and tax incentives for LTCI uptake (see Appendix 2.C for an in-depth overview of our data). The evidence – including one quasi-experimental study – shows that more lenient means-tested social benefits schemes either decrease LTCI demand or have no effect.[16] On the contrary, tax incentives[17] (and consequently lower prices) lead to greater willingness to insure, according to three quasi-experimental studies. Moreover, the impact of social benefit extensions and tax incentives on LTCI demand does not seem

14 Of course, the actual insurance value is also important. Increases in daily benefits and benefit periods, as well as decreases in the deductible period are associated with higher LTCI uptake according to a recent stated-preferences study (Akaichi et al. 2020).

15 Only one study (Swamy 2004) finds that having a financial advisor does not significantly change LTCI ownership.

16 This does not hold for Federal Partnership programs that protect a portion of an individual's assets that would otherwise need to be spent down in order to become eligible for Medicaid. Most research shows that these programs do not change coverage and are de facto a tax benefit for those who would have bought LTCI in any case (e.g., Bergquist et al. 2018).

17 There may be a differential effect of tax deductions and tax credits. Most studies explicitly focusing on tax deductions report a positive impact on uptake, whereas studies focusing on tax incentives in general do not.

to be equally distributed among the targeted population. Rather, tax incentives may predominantly benefit wealthier (Lin & Prince 2013) or healthier (Cornell & Grabowski 2018) individuals. Perceptions also seem to be important as uptake is generally lower among individuals who perceive public coverage to be more extensive (Kumar et al. 1995; McCall et al. 1998; Unruh et al. 2016), with only two studies reporting no significant effects (Brown et al. 2012; Swamy 2004). Similarly, framing of LTCI products is suggested to play a role in these decisions (Gottlieb & Mitchell 2015; Pincus et al. 2017).

Finally, Table 2.3 shows that expected availability of informal care may negatively impact LTCI uptake, although a majority of the studies finds no significant association. At the same time, Courbage and Roudaut (2008) show with an objective measure of predicted availability that informal care availability can also increase uptake. This may be because purchasing LTCI can protect family and friends from informal caregiving.

Table 2.3 Overview of findings by studies on contextual factors associated with LTCI uptake (number of quasi-experimental studies between brackets)

Factor	Association						Total
	Negative		None		Positive		
	#	%	#	%	#	%	#
Social benefits	4 (1)	40%	6 (0)	60%	0 (0)	0%	10 (1)
Tax subsidies (a)	0 (0)	0%	4 (0)	44%	5 (3)	56%	9 (3)
Informal care availability	4 (0)	31%	7 (0)	54%	2 (0)	15%	13 (0)

Note: (a) One study reports different associations of tax deductions and tax credits and has been counted under "none".

2.5.1.3. Why is LTCI uptake so low?

From our theoretical (Subsection 2.4.1) and empirical overview (Subsections 2.5.1.1 and 2.5.1.2) we infer four general explanations for the low uptake of private LTCI: (i) substitution by public LTCI or informal care; (ii) adverse selection; (iii) individual preferences that differ from those assumed in standard economic models of consumer behavior; (iv) financial illiteracy; and (v) discuss how these may relate to the distribution of LTCI uptake over the population.

(i) In line with theoretical predictions, there is strong evidence that private LTCI is to some extent substituted by public LTCI. LTCI may also be substituted with informal care, but this relationship is less clear cut. Our results suggests that both the number of children and the expected availability of informal care givers may decrease LTCI uptake, whereas marital status seems to have no impact on uptake. Potentially, these results reflect the fact that these measures are quite generic: if you have a partner or children this does not necessarily mean that they are able (and willing) to provide informal care. Alternatively, Coe, Goda and Van Houtven (2015) have shown that LTCI ownership by parents, can induce children to live further away from their parents and to work more. In other words, purchasing private LTCI may could lower ex post informal care expectations and the negative relationship may also reflect reverse causality.

(ii) As theoretically predicted, adverse selection could also play a role on the LTCI market, as the existence of private information has been proven both directly (Finkelstein & McGarry 2006) and indirectly (Gan et al. 2015) and as people seem fairly responsive to the price of LTCI (Cornell & Grabowski 2018; Costa-Font & Font 2009; Cramer & Jensen 2006; Goda 2011).

The empirical literature highlights three potential sources of private information: objective knowledge of LTC risks, subjective knowledge of LTC risks and subjective knowledge of health. First, some individuals know that they are objectively likely to have high LTC costs, for example because they suffer from a genetic diseases associated with higher LTC needs. These individuals are more likely to purchase LTCI (Oster et al. 2010). Second, individuals who expect to have LTC needs in the future take out more private LTCI. If this subjective risk assessment is accurate this would lead to adverse selection, but it is unclear whether this is actually the case.[18] Third, one would expect adverse selection to concentrate uptake among subjectively less healthy individuals, yet our review finds the opposite. Hence, some authors conclude that people do not realize that poor health can lead to LTC needs later in life (Browne & Zhou-Richter 2014). Another potential explanation is that subjectively healthier people may expect to live longer and associate longevity with LTC needs (Cramer & Jensen 2006), but it is unclear whether this is indeed the case.

In addition, some studies have analyzed whether dynamic adverse selection (i.e., individuals adversely select when receiving new information on their risk status) drives lapsing. These studies find higher LTC utilization among non-lapsers (Finkelstein et al. 2005; Konetzka & Luo 2011). However, this could also be due to ex post moral hazard. Moreover, Konetzka and Luo (2011) argue that such lapsing reflects personal finances and the availability of informal caregivers rather than private information.

Although adverse selection is taking place at the individual level, Finkelstein and McGarry (2006) show that the LTCI risk pool does not have a larger LTC risk than the population at large. This is unlikely to be a result of successful underwriting, since our review shows that ADL impairments – which are the main objective health factors used in underwriting – are not significantly associated with LTCI uptake. Instead, Finkelstein and McGarry (2006) show that adverse selection is compensated by the advantageous selection of low-risk individuals with strong insurance preferences.

(iii) Low uptake could also be driven by preferences that deviate from those typically assumed in economic models. For example, our results highlight that risk aversion does not unambiguously increase insurance, which contrasts with standard economic theory. Possibly, people perceive LTCI as a risky investment rather than as a risk-reducing insurance product. In other words, if LTC is not needed then premiums do not 'pay off' (Kunreuther et al. 2012). Additionally, our review shows that preferences for formal care impact LTCI uptake.[19] Specifically, preferences for informal care over formal care may decrease LTCI uptake.

Moreover, people may fear that insurers will not pay out, as distrust of insurance companies is associated with lower LTCI uptake. Such a trust relationship may be especially important as LTCI provides coverage against risks that are often in the far future. The fact that LTCI may only pay out in the future, may also trigger nonstandard time preferences or state-dependent utility preferences. Nonetheless, we found no empirical evidence about the impact of time preferences on insurance uptake.

Finally, most evidence for the theoretically suggested impact of state-dependent utility remains indirect. For example, using the HRS Finkelstein Luttmer and Notowidigdo (2013) show that marginal utility decreases when health decreases, but they do not directly link this to LTCI uptake. One study suggests that people who prefer to spend resources on care when ill over spending them on other goods and services when healthy are indeed more likely to purchase LTCI (Brown et al. 2012). Still, this result should be interpreted with caution as by explicitly referring to spending resources on LTC, this study may to some extent have measured preferences for LTCI itself rather than state dependent preferences.

(iv) People may find it difficult to make decisions on purchasing LTCI, which may cause them to deviate from expected utility maximization. This may be loss so for more financially literate individuals, who are consequently more likely to take out private LTCI. Additionally, in line with theoretical predictions of probability underweighting, our review shows that those who are aware of LTC risks purchase more insurance than those who do not. Finally, Lin and Prince (2016) show that wealthier individuals are also better able to

18 Friedberg et al. (2017) find LTC expectations not to be a significant predictor of actual LTC use later in life, whereas Finkelstein and McGarry (2006) find the opposite.

19 Bequest motives have also been left out of some standard economic predictions, even though they work to increase uptake, as is described theoretically and found empirically. As such, bequest motives only increase the discrepancy between prediction and actual uptake.

make use of sponsored LTCI plans, indicating that socio-economic status may to some extent reflect such decision-making ability.

(v) From our review it follows that uptake of LTCI differs across different subgroups of the population, and that it is likely to be concentrated among individuals with higher education, income and wealth. This may well be seen as a byproduct of the causes for low uptake. First, as most social benefit schemes are means-tested, crowding out should theoretically take place predominantly among individuals with low income and wealth (Brown & Finkelstein 2008). This is also what is observed empirically (Brown, Coe & Finkelstein 2007) and works to increase relative uptake among wealthier individuals. Second, if people use subjective health as a proxy for LTC and longevity risks, adverse selection can work to concentrate uptake among individuals with high socio-economic status individuals as these are relatively healthy. Third, it has been shown that preferences for insurance differ and are an important determinant of LTCI uptake (Browne & Zhou-Richter 2014; Cutler et al. 2008; Gan et al. 2015). These preferences are at least partially related to wealth, as research shows that wealthier individuals[20] (Finkelstein & McGarry 2006) are more likely to own LTCI, yet much less likely to enter a nursing home. Fourth, financial literacy could be correlated with socio-economic status and could thus lead to increased uptake among those with a higher socio-economic status.

2.5.2. Uptake of annuities

Table 2.4 provides an overview of all 44 included empirical studies on annuity uptake decisions. Clearly, these studies are more diverse than those analyzing LTCI decisions. Datasets consist of experimental data, survey data (often from independently developed surveys) and administrative datasets. This variety in empirical methods is also reflected in the GRADE quality of the studies: 6 studies are graded 'B', 27 'C' and 11 'D'. Moreover, sample restrictions concerning age are generally much more inclusive than for LTCI, as they may compromise all adult age groups.

Annuitization itself is measured in two ways. Many studies measure revealed preferences. Such studies either follow cohorts of individuals that retire and measure their annuitization decisions (e.g., Brown & Previtero 2014; Bütler & Teppa 2007; Hurd & Panis 2006) or use a survey to ask whether individuals own annuities (e.g., Pfarr & Schneider 2013; Schreiber & Weber 2016). Another strand of research uses hypothetical annuitization measures to elicit stated preferences (e.g., Knoller 2016; Wu et al. 2017). Occasionally, associations found by stated and revealed preferences point to different directions. When suited, we reflect on this.

Table 2.4 Overview of included studies on annuity uptake

Authors	#	Dataset	Country	N	Restrictions
Agnew, Anderson, Gerlach and Szykman (2008)	1	Experiment	US, VA	845 ind.	18-89 years old nonstudents
Ai et al. (2017)	2	Focus group	US, TX	n.a.	n.a.
Bateman et al. (2017)	3	Survey	Australia	923 ind.	gender and age quota
Benartzi, Previtero and Thaler (2011)	4	Administrative dataset	US	103,516 ind.	50-75 years old with over 5 years of job tenure and balance over $5k retired between 2002 and 2008

(continued on next page)

20 As well as individuals who use preventive health services and individuals who always wear their seatbelts (Cutler et al. 2008; Finkelstein & McGarry 2006).

Table 2.4 (continued)

Authors	#	Dataset	Country	N	Restrictions
Bernheim (1991)	5	LRHS (1975 wave)	US	2,091 ind.	64-69 years old with wealth under $500k not widowed not eligible for government pensions
Beshears, Choi, Laibson, Madrian and Zeldes (2014) (a)	6	Survey	US	5,130 ind.	50-75 years old
Bockweg, Ponds, Steenbeek and Vonken (2016) (a)	7	Survey	Netherlands	3,161 ind.	members of an occupational pension plan
Brown (2001)	8	HRS (wave 1)	US	869 ind.	51-61 years old employed and with a DC plan
Brown, Kapteyn, Luttmer, Mitchell and Samek (2017)	9	Survey	US	4,549 ind.	over 18 years old
Brown, Kapteyn, Luttmer and Mitchell (2017) (a)	10	Survey	US	2,112 ind.	over 18 years old
Brown, Kling, Mullainathan and Wrobel (2013)	11	Survey	US	4,055 ind.	over 50 years old
Brown and Previtero (2014)	12	Administrative dataset	US	27,231 ind.	retired between 2002 and 2008
Bütler, Staubli and Zito (2013)†	13	Administrative dataset	Switzerland	15,312 ind.	over 60 years old men retired between 2001 and 2005
Bütler and Teppa (2007)	14	Administrative dataset	Switzerland	4,544 ind.	retired between 1996 and 2006
Cannon, Tonks and Yuille (2016)	15	ABI QLB and QPA Surveys	UK	27 quarters	n.a.
Cappelletti, Guazzarotti and Tommasino (2013)	16	SHWI (2008 wave)	Italy	4,750 ind.	15-65 years old
Chalmers and Reuter (2012)	17	Administrative dataset	US, OR	31,809 ind.	retired between 1990 and 2002 public employees
Charupat and Milevsky (2001)	18	Data on annuity quotes and mortality	Canada	n.a.	n.a.
Chou, Inkmann, Van Kippersluis and Chan (2016)	19	Survey	Hong Kong	1,066 ind.	40-64 years old working full-time

(continued on next page)

Table 2.4 (continued)

Authors	#	Dataset	Country	N	Restrictions
Clark, Morrill and Vanderweide (2014)	20	Administrative dataset	US, NC	46,913 ind.	under 50 years old and terminated a plan in 2007 or 2008
Cutler et al. (2008) (b)	21	AHEAD (wave 2)	US	7,183 ind.	65-90 years old
Doyle, Mitchell and Piggott (2004)	22	Data on mortality, annuity payments and interest rates	Singapore and Australia	n.a.	n.a.
Finkelstein and Poterba (2002)	23	Data on mortality, annuity payments and interest rates	UK	n.a.	n.a.
Friedman and Warshawsky (1990)	24	Data on mortality and annuity payments	US	n.a.	n.a.
Guillemette, Martin, Cummings and James (2016)	25	Survey	US	5,074 ind.	n.a.
Hagen (2015)	26	Administrative dataset	Sweden	73,555 ind.	retired between 2008 and 2010 with parents from Sweden
Hurd and Panis (2006)	27	HRS (wave 1-5)	US	3,651 ind.	over 50 years old retired between 1992 and 2000
Hurwitz and Sade (2017)	28	Administrative dataset	Israel	1,556 ind.	retired between 2009 and 2013 with balance > 500K NIS
Inkmann, Lopes and Michaelides (2011)	29	ELSA (wave 1)	UK, England	5,233 ind.	over 50 years old
Knoller (2016) (a)	30	Experiment	Germany	140 ind.	students
Knoller, Kraut and Schoenmaekers (2016)	31	Administrative dataset	Japan	15,180 policies	n.a.
Lee (2016)	32	Administrative dataset	South Korea	32,867 policies	deferred annuities that matured between 2008 and 2011
Mitchell et al. (1999)	33	Data on mortality, annuity payments and interest rates	US	n.a.	n.a.
Nosi, D'Agostino, Pagliuca and Pratesi (2017)	34	Survey	Italy	7,840 ind.	25-35 years old without private pension

(continued on next page)

Table 2.4 (continued)

Authors	#	Dataset	Country	N	Restrictions
Payne, Sagara, Shu, Appelt and Johnson (2013) (a)	35	Survey	US	514 ind.	45-65 years old
Pfarr and Schneider (2013)	36	SAVE (wave 2005-2009)	Germany	5,242 ind.	under 65 years old, working, married and eligible for Riester pensions
Previtero (2014)	37	Administrative dataset	US	103,516 ind.	retired between 2002 and 2008
Schooley-Pettis and Worden (2013)	38	Survey	US	987 ind.	n.a.
Schreiber and Weber (2016)	39	Survey	Germany	3,077 ind.	18-86 years old
Shu, Zeithammer and Payne (2018)	40	Survey	US	1,020 ind.	40-65 years old
Teppa (2011)	41	DNB Household Survey (2005)	Netherlands	816 ind.	16-65 years old
Van der Cruijsen and Jonker (2016)	42	Survey	Netherlands	2,082 ind.	over 25 years old
Wuppermann (2017)	43	ELSA (wave 0-4)	UK, England	8,204 ind.	n.a.
Ziegelmeyer and Nick (2013)	44	SAVE (wave 2010)	Germany	1,432 ind.	working and eligible for Riester pensions

Notes: (a) Quasi-experimental study (highest level of evidence available). (b) Also analyzes LTCI uptake.

2.5.2.1. Individual factors

Table 2.5 displays the main findings of the empirical studies on individual factors associated with annuity uptake. Below we reflect on these factors one-by-one. Appendix 2.D shows exactly which associations were found by which studies and distinguishes between the results of revealed and stated preferences.

As to gender and age, uptake patterns displayed in Table 2.5 are broadly similar to those of LTCI, including the differences between stated and revealed preference studies. Women may be more likely to opt for annuities than men, although the majority of included studies finds no significant difference. Again this may highlight the fact that without gender-based pricing annuities are effectively cheaper for women, who on average live longer. Gender-based risk differences are currently not allowed to be translated into premiums in the EU (European Union 2004) and in employer-sponsored plans in the US (Arizona Governing Committee for Tax Deferred Annuity and Deferred Compensation Plans v. Norris 1983). The impact of age on uptake remains difficult to interpret. To some extent, age effects may reflect cohort effects of studies employing age-cohorts, although there are admittedly fewer doing so for annuities than for LTCI. Even so, there is no clear pattern in the effects summarized in Table 2.5, and the two studies analyzing squared age effects retrieve different results: one reports a positive effect of age squared (Clark et al. 2014), whereas the other finds no significant effect (Teppa 2011). Finally, ethnicity may impact uptake. Yet, we find only one study (Hurd & Panis 2006) that reports a positive association between being black and annuitization.

Table 2.5 Overview of findings by studies on individual factors associated with annuity uptake

Factor	Association						Total
	Negative		None		Positive		
	#	%	#	%	#	%	#
Demographics							
Female (a)	4	17%	12	52%	7	30%	23
Age	8	36%	7	32%	7	32%	22
Non-white	0	0%	1	50%	1	50%	2
Socio-economic status							
Education	0	0%	14	82%	3	18%	17
Income (a)	1	7%	9	64%	4	29%	14
Home ownership	0	0%	4	100%	0	0%	4
Wealth (a)	1	7%	5	33%	9	60%	15
Family							
Number of children (b)	1	8%	12	92%	0	0%	13
Married (c)	2	12%	15	88%	0	0%	17
Bequest motive	1	14%	5	71%	1	14%	7
Subjective risk							
Subjective health	0	0%	6	67%	3	33%	9
Subjective longevity (a)	1	8%	7	58%	4	33%	12
Objective risk Longevity (d)	0	0%	2	50%	2	50%	4
Preferences							
Risk aversion	3	27%	5	45%	3	27%	11
Stock market participation	1	17%	3	50%	2	33%	6
Patience	0	0%	0	0%	4	100%	4
Trust insurer	0	0%	1	50%	1	50%	2
Understanding Financial literacy (e)	2	20%	4	40%	4	40%	10
Salience Awareness of longevity risk	0	0%	0	0%	2	100%	2

Notes: (a) Discrepancy in results of stated and revealed preferences studies. (b) Three studies report having children (or not) rather than the number of children. (c) Three studies report different associations for married individuals compared to individuals who are single, divorced, or widowed and have been counted under "none". (d) One study reports different associations for two measures of ex ante mortality and has been counted under "none". (e) One study reports different associations for three different measures of financial literacy and has been counted under "none".

Table 2.5 also shows that wealth is generally positively associated with annuity uptake, even though a large share of the stated preference studies find no significant association. At the same time, income and annuity uptake may be positively associated, but the majority of the studies reports no significant association. This effect is driven by stated preference studies, suggesting that although stated preferences may be similar, actual uptake may differ along income and wealth. Education and homeownership[21] are found to be of limited relevance in explaining annuitization. The low number of studies finding

21 One study looking into the impact of home equity rather than home ownership finds that increases in home equity may decrease annuity uptake among the lowest home equity quintiles (Guillemette et al. 2016).

any effect of education is markedly different from the strong association found with LTCI uptake and consistent between stated preferences and revealed preference studies.

As to the impact of family characteristics, Table 2.5 shows that most studies do not find any effect of either having children[22], being married[23] or having bequest motives. This is clearly different from theoretical predictions that families could offer efficient risk pools. Still, our results do not rule out that some individuals pursue theoretically predicted strategic bequest motives. If some individuals have strategic negative bequest motives (increasing uptake) this could on average offset other people's positive bequest motives (decreasing uptake) such that the aggregate effect of bequest motives is indistinguishable from zero.

In addition, Table 2.5 highlights the potential importance of subjective and objective risk factors in annuity decisions. One third of the included studies find that individuals with better subjective health and subjective longevity are more likely to purchase annuities, but the majority of studies does not find evidence of a significant relationship. Particularly, none of the revealed preference studies included reports a significant association. Few studies analyze the relationship between objective longevity risks and annuity uptake. One study notes that the number of chronic illnesses has no impact on annuity uptake (Chou et al. 2016). Studies analyzing realized longevity for historic annuity uptake all find that those who purchased annuities lived longer. Additionally, there is some evidence that the longevity of parents is also positively associated with annuity uptake.[24] All in all, the evidence available suggests that experienced health and objective longevity are positively associated with annuity uptake.

Furthermore, there is no convincing evidence that risk preferences are associated with uptake decisions. First, the evidence we map in Table 2.5 does not show clear association of risk aversion or stock market participation with annuity holding. Second, another indicator of risky behavior, namely smoking, does not seem to be associated with annuity uptake (Guillemette et al. 2016; Hurwitz & Sade 2017). Third, even though some studies find a positive relationship between annuity uptake and health insurance ownership (Hurd & Panis 2006) or LTCI ownership (Pfarr & Schneider 2013), others do not (Chou et al. 2016). Additionally, several studies found patience and personal trust in the insurance company[25] positively associated with annuity uptake.

Next, Table 2.5 shows that financial literacy – again measured as knowledge of probabilities, inflation, compound interest and risk diversification – may increase annuity uptake.[26] [27] In addition, two other studies find a positive association between a principal component of education, financial literacy and cognitive intactness on the one hand and annuity valuation on the other (Brown et al. 2017b, 2017a). Using a financial advisor is also associated with higher uptake (Pfarr & Schneider 2013). Even so, studies using subjective measures of financial literacy find that these are associated with lower uptake of annuity products (Bateman et al. 2017; Bockweg et al. 2016) or have no effect (Knoller 2016; Shu et al. 2018; Van der Cruijsen & Jonker 2016). Potentially because these measures indicate financial (over)confidence, rather than actual financial literacy (Bateman et al. 2017).

Finally, Table 2.5 displays risk awareness as a relevant factor in annuity uptake. Two studies highlight that such awareness associated positively with annuity uptake. In addition, two quasi-experimental studies show that salience of longevity risks – achieved by asking respondents about their subjective longevity (Payne et al. 2013) or by showing a mortality graph (Beshears et al. 2014) before making an annuity uptake decision – increases uptake as well.

22 One study shows a positive impact of having dependent children on annuity uptake (Bütler & Teppa 2007).
23 There are no systematic differences when married individuals are compared to single, divorced or widowed individuals
24 Two studies looking at job mortality find a positive association (Cutler et al. 2008) and no association (Hurwitz & Sade 2017) with annuity uptake.
25 One study analyzing the impact of objective financial strength of a company finds no association (Chou et al. 2016).
26 Moreover, one of the studies that note a negative impact of financial literacy on uptake finds a positive impact of specific product knowledge (Chou et al. 2016).
27 A hypothetical study that corrects for survey attention also finds that survey attention increases hypothetical annuity uptake (Bateman et al. 2017).

2.5.2.2. Contextual factors

Contextual factors that are associated with annuity uptake are summarized in Table 2.6. Contrary to theoretical predictions, not all evidence shows that social benefits may decrease annuity uptake. That such substitution is not observed here, may be due to the fact that in many countries social benefits are additional to other pension rights, thus offering basic financial security for the majority of the population (Schreiber & Weber 2016). Public policy seems to mainly impact uptake through setting annuitization rules. First, Cannon et al. (2016) show that flexibilization of mandatory annuitization led to lower annuity uptake in the UK. Clearly, annuitizing by default increases uptake, potentially because it decreases procrastination and makes annuitizing simpler.[28] Second, tax incentives can also increase annuity uptake as shown in Table 2.6.[29]

Annuity equivalent wealth is also positively associated with uptake, as shown in Table 2.6.[30] Similarly some studies have argued that uptake is low because policies have too little value compared to their costs (Brown 2001; Doyle et al. 2004; Mitchell et al. 1999). One study analyzing the perceived fairness of a policy reports similar results for subjective policy value (Shu et al. 2018). The relative value of annuities can also impact uptake. Table 2.6 shows that a higher return on investment for other investment products can decrease the uptake of annuities. Although other investments can indeed serve as investment substitutes, overreliance on recent stock market developments in determining investment portfolios induces individuals to underinvest in annuities and leads to welfare losses (Previtero 2014).

Table 2.6 Overview of findings by studies on contextual factors associated with annuity uptake (number of quasi-experimental studies between brackets)

Factor	Association						Total
	Negative		None		Positive		
	#	%	#	%	#	%	#
Social benefits (a)	1 (0)	33%	2 (0)	67%	0 (0)	0%	3 (0)
Tax incentives	0 (0)	0%	0 (0)	0%	3 (0)	100%	3 (0)
Annuity equivalent worth	1 (0)	17%	0 (0)	0%	5 (1)	83%	6 (1)
Return on investments	3 (0)	75%	1 (0)	25%	0 (0)	0%	4 (0)
Annuity as defaults	0 (0)	0%	1 (0)	75%	4 (0)	80%	5 (0)
Framing as investment	4 (1)	80%	1 (1)	20%	0 (0)	0%	5 (2)
Protections (b)	0 (0)	0%	1 (0)	20%	4 (1)	80%	5 (1)

Notes: (a) One study reports different associations of different social benefit schemes and has been counted under "none". (b) One study reports a positive association with period guarantees and a negative association with inflation protection and has been counted under "none".

In addition, Table 2.6 shows that framing can be of great importance in uptake decisions. Multiple studies show that framing annuities as investment, rather than as insurance of consumption, decreases uptake. This is likely because investment framing emphasizes the possibility that people pay more annuity premiums than they will receive in terms of benefits, thus triggering loss aversion (Brown, Kling, Mullainathan & Wrobel 2008). Consequently, evidence including one quasi-experimental study suggests that annuities with additional protections – such as period guarantees, principal protections, or inflation coverage – can increase uptake. In line with this, one quasi-experimental study shows that framing annuities in terms of lack of flexibility and control significantly reduces uptake (Beshears et al. 2014). Other framing aspects may also be of importance, as another quasi-experimental study shows that using a "live to" (rather than "die by") frame (Payne

28 Procrastination is associated with lower uptake (Brown & Previtero 2014), whereas two studies find that simplicity of the product is associated with higher uptake (Brown, Kapteyn, Luttmer, Mitchell, et al. 2017) or not associated with uptake (Bockweg et al. 2016).
29 Design of incentives is important, as poorly designed incentives can decrease the relative attractiveness of annuities (Charupat & Milevsky 2001).
30 One study suggests that this relationship is non-linear, as it finds a statistically significant positive squared effect (Clark et al. 2014)

et al. 2013) increases uptake. Framing a specific annuity goal may (Knoller 2016) or may not (Brown et al. 2013) increase uptake. Finally, one study shows that people annuitize less when risks are more ambiguous and when the choice tasks is more complex (i.e., more information is offered) (Brown, Kapteyn, Luttmer, Mitchell, et al. 2017).

2.5.2.3. Why is annuity uptake so low?

From our theoretical (Subsection 2.4.3) and empirical overview (Subsections 2.5.2.1 and 2.5.2.2) we infer the same explanations for low uptake of annuities as those inferred earlier for LTCI: (i) substitution by social benefits; (ii) adverse selection; (iii) individual preferences that differ from those assumed in standard economic models of consumer behavior; and (iv) financial illiteracy. Subsequently, (v) we discuss how these may relate to the distribution of annuity uptake over the population.

(i) As theoretically predicted, substitution by social benefits can decrease annuity uptake. Whether it actually does, however, seems to depend crucially on the design of the social benefit system. If social benefits are used only as a safety net for those worst off, then it may substitute for annuity uptake. If social benefits provide a base consumption for all retirees, substitution does not seem to take place.

In addition, other investments have theoretically been proposed to substitute for annuity uptake (Hainaut & Devolder 2006). In practice, we find evidence that people purchase annuities less when stock indices are high. However, this does not seem to indicate that stock market investments actually substitute for annuities. Rather, overreliance on recent stock price increases induces people to overestimate returns on annuities and to underannuitize for retirement altogether (Previtero 2014). Hence, although stock prices are associated with lower uptake, it is not clear to what extent this is driven by substitution and to what extent by limited rationality.

(ii) Adverse selection seems to play a role in the annuity market, as predicted theoretically. Our results highlight that those who take up annuities have a higher longevity risk; they may be subjectively healthier, may have a higher subjective longevity risk and they live objectively longer. Additionally, studies analyzing annuity equivalent worth – or policy value – have shown that this is lower due to adverse selection (Brown 2001; Doyle et al. 2004; Mitchell et al. 1999).

(iii) Nonstandard preferences may also explain lower than expected annuity demand. In line with theoretical predictions, our overview of empirical studies suggests that higher levels of patience are associated with higher levels of annuity. However, our overview also highlights discrepancies between theoretical and empirical studies. First, there is no evidence that risk aversion or any proxy thereof is associated with higher annuity uptake. Second, bequest motives do not seem to increase annuity uptake, although this may indicate that some parents use bequests to strategically influence behavior of their children.

(iv) As for LTCI, it seems that annuity uptake decisions are difficult. Specifically, higher financial literacy and greater salience of longevity risks lead to increased annuity uptake, suggesting that those with greater knowledge or risk awareness are better protected against longevity risks. Additionally, one study has highlighted that people who are prone to procrastinate are less likely to own annuities (Brown & Previtero 2014). Moreover, uptake decisions seem to be guided by contextual defaults and framing, rather than by expected utility maximization. Finally, trust in insurance companies is associated with higher annuity uptake and lack thereof may thus contribute to low uptake levels.

(v) From our review it follows that uptake of annuities differs across different subgroups of the population, as does the uptake of LTCI. Even though substitution by social benefits (among lower income individuals) plays a role in annuity uptake, we find that uptake is concentrated among individuals with high wealth (and likely also high income). Following our other explanations for low uptake we infer that these individuals may (a) have better subjective health and higher longevity and adversely select into the annuity market; (b) simply have other preferences than those with lower wealth, although this is not supported by stated preference studies; and/or (c) be better able to judge the value of those products.

2.6. Discussion

Our study provides an overview of the evidence from revealed preference studies, stated preference studies and theoretical models of demand for LTCI and annuities, integrating the limited quasi-experimental research available. Altogether, the evidence consistently suggests that low uptake follows from substitution, adverse selection, nonstandard preferences and limited rationality. Hence, our findings are unlikely to reflect measurement errors that are specific to these research methods. Rather, we show that employing different methods to answer the pressing LTCI and annuity puzzles renders qualitatively similar results on aggregate.

In addition, combining our results may provide valuable insight into the factors that impact insurance decisions for late-in-life risks in general. Particularly, this may elucidate to what extent groups with low LTCI and annuity uptake may overlap. Therefore, Table 2.7 summarizes which specific aspects limit uptake for both LTCI and annuities. Uptake of both LTCI and annuities is lower for individuals that (i) are eligible for public policies that can substitute for private insurance; (ii) that are subjectively less healthy; (iii) that have lower trust in insurance companies; and (iv) that are less financially literate or risk aware.

Table 2.7 Explanations for low uptake of LTCI and annuities and their similarities

	LTCI	Annuity	Similarities
Substitution	• Is substituted by social benefits that provide a safety net only • May be substituted by informal care availability	• Is substituted by social benefits that provide a safety net only • Is not substituted by intra-family risk pooling	• Social benefits that provide a safety net only may substitute for private insurance
Adverse selection	• Individuals with subjectively better health have higher uptake • Individuals with higher subjective LTC risks have higher uptake • Individuals with objectively worse health do not have higher uptake	• Individuals with subjectively better health have higher uptake • Individuals with higher subjective longevity risks have higher uptake • Individuals with objectively higher longevity risks have higher uptake	• Individuals with subjectively better health have higher uptake
Nonstandard preferences	• Trust in insurers is associated with higher uptake • Risk aversion is not associated with uptake	• Trust in insurers is associated with higher uptake • Risk aversion is not associated with uptake	• Trust in insurers is associated with higher uptake • Risk aversion is not associated with uptake
Limited rationality	• Financial literacy is associated with higher uptake • Risk awareness is associated with higher uptake	• Financial literacy is associated with higher uptake • Risk awareness is associated with higher uptake	• Financial literacy is associated with higher uptake • Risk awareness is associated with higher uptake

These results may contain lessons for integrated products that insure simultaneously against LTC and longevity risks. Such life-care annuities (LCAs) have been proposed on a theoretical basis to diminish adverse selection by combining negatively correlated LTC and longevity risks in one product (Murtaugh et al. 2001).[31] Although in the US uptake of annuities with LTC riders seems promising, it is unclear whether these products indeed broaden the market. Currently, only one study has analyzed demand for LCAs directly (Wu et al. 2018). This study finds no evidence of selection effects in purchase decisions for hypothetic integrated products, but also highlights that uptake is impacted by risk awareness as well as by ease of financial knowledge acquisition.

31 This has been disputed by Zhou-Richter and Gründl (2011) who argue that long-term care and longevity risks are positively correlated and that LCAs hence may offer even more room for adverse selection.

In particular, we speculate that integrated products are unlikely to substantially expand the market as a whole for three reasons. First, uptake is not only limited by adverse selection, but also impacted by substitution, nonstandard preferences and limited rationality. Second, all these explanations seem to result in a concentration of demand among healthy individuals with higher wealth, making it difficult to expand the market for LTCI and longevity insurance products to a broader population. Third, an integrated product may turn out to be more complex than two separate products and may thus work to decrease uptake amongst the least financial literate. Nonetheless, future work remains necessary to better understand the viability of such integrated products.

2.7. Conclusion and recommendations

Our systematic literature review shows that similar factors hinder the uptake of both LTCI and annuities. Specifically, we find that uptake is lowered by substitution by social security, adverse selection, nonstandard preferences and limited rationality due to low financial literacy and risk unawareness. Moreover, these factors may also explain why insurance holding is concentrated among individuals with high wealth and good subjective health. An integrated product – only focusing on solving adverse selection issues – is unlikely to solve other aspects that limit uptake. Particularly, our results show that uptake for integrated products is likely to remain concentrated among wealthier and subjectively healthier individuals.

Further research is warranted to better understand the dynamics of LTCI and annuity uptake. Specifically, it is worth analyzing to what extent our findings can indeed explain the concentration of uptake among individuals with good subjective health and high wealth. The fact that uptake of private insurance is unequally distributed also has important consequences for policy makers. In so far as low uptake reflects an active choice to substitute for private insurance or reflects a dislike of private insurance, it echoes individual preferences and requires no action. However, to the extent that it reflects adverse selection or limited rationality, lower uptake is a product of underlying inequalities in health or longevity and related unequal capabilities, and that may warrant policy interventions.

If the goal is to increase insurance uptake on private LTCI or annuity markets, policy makers and insurers could undertake several actions to create a more inclusive insurance market. First, individuals with low financial literacy should be empowered to make their own insurance decisions. This may not only be achieved through educational policies that increase financial literacy and hence understanding of LTCI and annuity products. In addition, complexity of the choice environment should be reduced by making insurance policies easier to comprehend and by reducing the number of policy options. Second, risk awareness increases insurance uptake; policy makers and insurers could thus focus on raising awareness of LTC and longevity risks. Particularly, governments should be clear about what social benefits do and do not reimburse and about what contribution is expected from citizens themselves. Even though large-scale awareness campaign sometimes have limited impact (Iwasaki et al. 2010), such campaigns are easy and relatively cheap to implement. Third, since our results show that distrust of insurers additionally drives low uptake, government regulation or insurance standards that protect insured persons by guaranteeing the pay out of fair claims may help to increase uptake. Fourth, evidence on the importance of perceptions, framing and defaults suggests that these may provide effective nudges for increasing insurance uptake (for an illustration, see: Bonsang & Costa-Font 2020). In addition, offering products with guaranteed pay-outs when the insured risk does not (fully) materialize may prove particularly effective.

Finally, the fact that those with lower subjective health, risk awareness or financial literacy buy predictably less protection against late-in-life risks may provide an argument for stronger government intervention. Particularly, governments may aim not only to safeguard individual freedom of choice, but also to protect their citizens from major financial risks. Hence, compulsory coverage – through an individual mandate for those not-covered by social insurance schemes or through an extension of social insurance schemes – may be warranted.

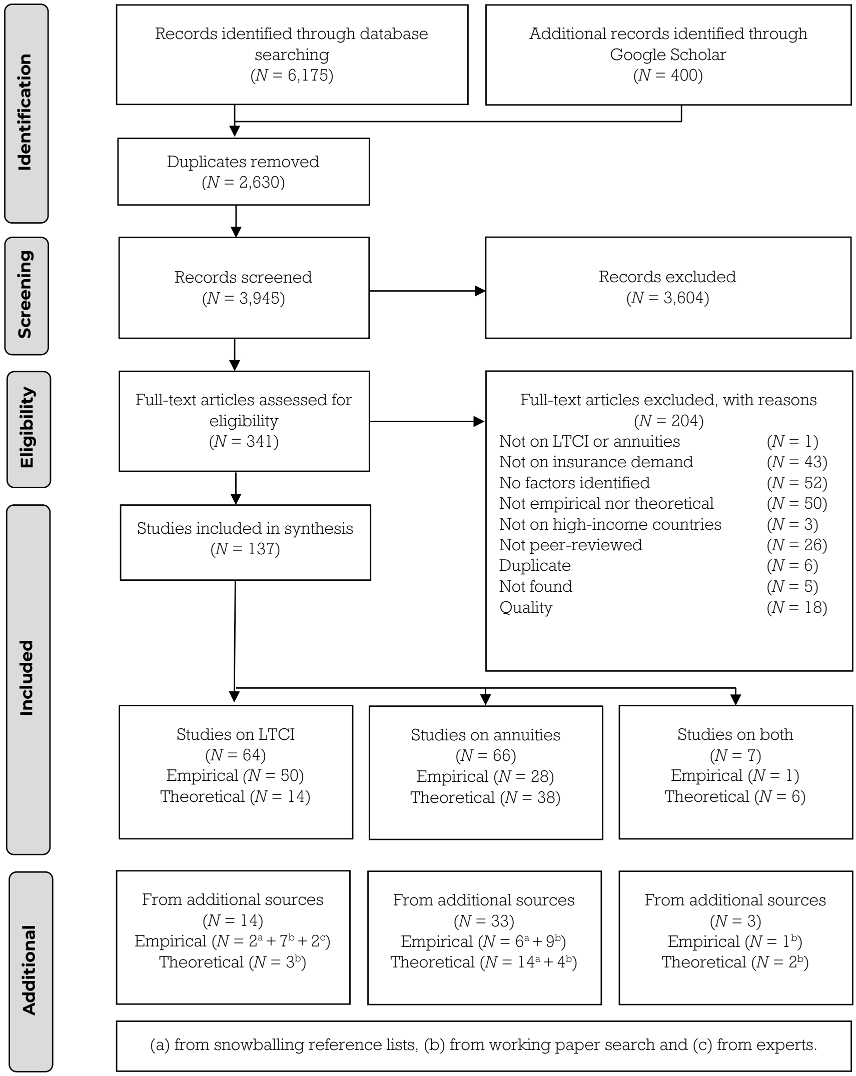
2.8. Appendices

A. Search string Embase.com

(((longevity/de OR ‘long term care’/de OR ‘elderly care’/exp OR retirement/de OR pensioner/de OR ‘nursing home’/de) AND (‘insurance’/de OR ‘social insurance’/de OR ‘social security’/de)) OR (((longevit* OR long-term-care OR longterm-care OR life OR ltc OR pension* OR retirement* OR nursing-home*) NEAR/6 (insur* OR annuit* OR Social-securit*)) OR ltci):ab,ti) AND (‘decision making’/de OR ‘purchasing’/de OR ‘attitude’/de OR ‘attitude to aging’/de OR ‘attitude to disability’/de OR ‘attitude to death’/de OR ‘attitude to life’/de OR ‘attitude to illness’/de OR ‘attitude to health’/de OR ‘consumer attitude’/de OR ‘family attitude’/exp OR motivation/de OR ‘decision support system’/de OR consumer/de OR (((decision* OR decid* OR uptake OR nonuptake OR purchase* OR nonpurchase* OR why OR buy OR buying OR reason* OR motivation* OR take-up OR choos* OR choice* OR procure OR willing* OR persua* OR selling OR crowd*-out* OR puzzle* OR obtain* OR select OR selecting OR selection OR take OR taking OR get OR getting OR interes* OR acquire* OR acquisition* OR afford* OR abilit* OR able OR pay OR paying OR preference* OR substit* OR exchang* OR replac* OR self-control* OR discount* OR invest* OR reference* OR consum* OR Participat* OR attain* OR wtp OR value* OR worth OR utilit* OR attitude* OR belief* OR confidence* OR overconfiden* OR confident OR trust* OR expectation* OR estimate* OR probabilit* OR weighting OR weighing OR bias* OR predispos* OR prejudice* OR approximat* OR guess OR assess* OR evaluat* OR uncertain* OR ambigu* OR attention* OR focus* OR sensitivit* OR concern OR concerns OR behav* OR perception* OR perceive* OR factor* OR salien* OR capacit* OR access* OR framing OR emotion* OR default OR familiar* OR pressure OR market* OR incentiv* OR disincentiv* OR barrier* OR facilitator*) NEAR/6 (insur* OR long-term-care-insurance* OR annuit*))):ab,ti) NOT ([Conference Abstract]/lim OR [Letter]/lim OR [Note]/lim OR [Editorial]/lim) AND [english]/lim

B. Individual and contextual level empirical evidence on LTCI uptake

PRISMA 2009 Flow Diagram



Note: From Moher, Liberati, Tetzlaff, Altman and The PRISMA Group (2009).

C. Individual and contextual level empirical evidence on LTCI uptake

Table 2.C1 Overview of findings by studies on individual factors associated with LTCI uptake

Factor	Association: Negative	Association: None	Association: Positive
Female	**4**	**20**	**13**
Stated preferences	3 • Allaire et al. (2016) • Swamy (2004) • Stevenson, Frank and Tau (2009)	7 • Ameriks, Briggs, Caplin, Shapiro and Tonetti (2018) • Brau, Bruni and Pinna (2010) • Costa-Font and Font (2009) • Costa-Font and Rovira-Forns (2008) • He and Chou (2020) • Kennedy, Gimm and Glazier (2016) • Wu, Bateman, Stevens and Thorp (2017)	0
Revealed preferences	1 • Brau and Bruni (2008)	13 • Caro, Porell and Kwan (2011) • Courbage and Roudaut (2008) • Cramer and Jensen (2006) • Friedberg, Hou, Sun and Webb (2017) • Gousia (2016) • Gottlieb and Mitchell (2015) • Jiménez-Martín, Labeaga-Azcona and Vilaplana-Prieto (2016) • McGarry, Temkin-Greener and Li (2014) • Mellor (2000) • Mellor (2001) • Schaber and Stum (2007) • Sloan and Norton (1997) • Stum (2008)	13 • Barnett and Stum (2013) • Bernet (2004) • Chatterjee and Fan (2017) • Konetzka and Luo (2011) • Kumar, Cohen, Bishop and Wallack (1995) • Li and Jensen (2012) • McCall, Mangle, Bauer and Knickman (1998) • McGarry, Temkin-Greener, Chapman, Grabowski and Li (2016) • McGarry, Temkin-Greener, Grabowski, Chapman and Li (2018) • McNamara and Lee (2004) • Pinquet, Guillén and Ayuso (2011) • Unruh, Stevenson, Frank, Cohen and Grabowski (2016) • Van Houtven, Coe and Konetzka (2015)
Age	**8**	**18**	**11**
Stated preferences	3 • Brau and Bruni (2008) • Brau et al. (2010) • Costa-Font and Font (2009)	2 • Ameriks et al. (2018) • Wu et al. (2017)	2 • Kennedy et al. (2016) • Pincus, Hopewood and Mills (2017)

(continued on next page)

Table 2.C1 (continued)

Factor	Association		
	Negative	None	Positive
Revealed preferences	5 • Friedberg et al. (2017) • He and Chou (2020) • Konetzka and Luo (2011) • Kumar et al. (1995) • Swamy (2004)	16 • Caro et al. (2011) • Chatterjee and Fan (2017) • Courtemanche and He (2009) • Gottlieb and Mitchell (2015) • Jiménez-Martín et al. (2016) • Li and Jensen (2012) • McGarry et al. (2014) • McGarry et al. (2016) • McNamara and Lee (2004) • Mellor (2001) • Sloan and Norton (1997) (a) • Stevenson et al. (2009) • Stum (2008) • Unruh et al. (2016) • Van Houtven et al. (2015) (b) • Zhou-Richter, Browne and Gründl (2010)	9 • Barnett and Stum (2013) • Bernet (2004) • Courbage and Roudaut (2008) • Doerpinghaus and Gustavson (2002) • Gousia (2016) • McCall et al. (1998) • McGarry et al. (2018) • Mellor (2000) • Schaber and Stum (2007)
Non-white	**1**	**13**	**2**
Stated preferences	1 • Kennedy et al. (2016)	1 • Allaire et al. (2016)	0
Revealed preferences	0	12 • Cramer and Jensen (2006) (c) • Gottlieb and Mitchell (2015) • Konetzka and Luo (2011) (c) • Li and Jensen (2012) (c) • McGarry et al. (2014) (c) • McGarry et al. (2016) (c) • McGarry et al. (2018) (c) • McNamara and Lee (2004) (c) • Sloan and Norton (1997) • Stevenson et al. (2009) (c) • Swamy (2004) • Van Houtven et al. (2015) (c)	2 • Bernet (2004) • Caro et al. (2011)
Education	**2**	**10**	**18**
Stated preferences	0	4 • Allaire et al. (2016) • Ameriks et al. (2018) • Brau et al. (2010) • Costa-Font and Rovira-Forns (2008)	2 • Brau and Bruni (2008) • He and Chou (2020)
Revealed preferences	2 • Gousia (2016) • Kumar et al. (1995)	6 • Barnett and Stum (2013) • Courbage and Roudaut (2008) • Friedberg et al. (2017) • Li and Jensen (2012) • McGarry et al. (2018) • Swamy (2004)	16 • Bernet (2004) • Caro et al. (2011) • Chatterjee and Fan (2017) • Cramer and Jensen (2006) • Jiménez-Martín et al. (2016) • Gottlieb and Mitchell (2015) • Konetzka and Luo (2011) • McCall et al. (1998) • McGarry et al. (2014) • McGarry et al. (2016) • McNamara and Lee (2004) • Mellor (2000) • Mellor (2001) • Sloan and Norton (1997) • Unruh et al. (2016) • Van Houtven et al. (2015)
Income	**0**	**14**	**22**

(continued on next page)

Table 2.C1 (continued)

Factor	Association		
	Negative	**None**	**Positive**
Stated preferences		2 • Ameriks et al. (2018) • Costa-Font and Font (2009)	5 • Allaire et al. (2016) • Brau and Bruni (2008) • Brau et al. (2010) • Costa-Font and Rovira-Forns (2008) • Kennedy et al. (2016)
Revealed preferences	0	12 • Browne and Zhou-Richter (2014) • Courbage and Roudaut (2008) • Courtemanche and He (2009) • Doerpinghaus and Gustavson (2002) • Friedberg et al. (2017) • Li and Jensen (2012) • McCall et al. (1998) • Sloan and Norton (1997) • Stevenson et al. (2009) • Stum (2008) • Swamy (2004) • Unruh et al. (2016)	17 • Barnett and Stum (2013) • Bernet (2004) • Caro et al. (2011) • Chatterjee and Fan (2017) • Cramer and Jensen (2006) • Jiménez-Martín et al. (2016) • Konetzka and Luo (2011) • Kumar et al. (1995) • McGarry et al. (2014) • McGarry et al. (2016) • McNamara and Lee (2004) • Mellor (2000) • Mellor (2001) • Nixon (2014) • Schaber and Stum (2007) • Van Houtven et al. (2015) • Zhou-Richter et al. (2010)
Home equity	**2**	**2**	**0**
Stated preferences	1 • Costa-Font and Rovira-Forns (2008)	1 • Wu et al. (2017)	0
Revealed preferences	1 • Boyer, de Donder, Fluet, Leroux and Michaud (2017)	1 • Stevenson et al. (2009)	0
Wealth	**1**	**10**	**16**
Stated preferences	0	2 • Ameriks et al. (2018) • Costa-Font and Rovira-Forns (2008)	2 • Allaire et al. (2016) • He and Chou (2020)
Revealed preferences	1 • Barnett and Stum (2013)	• 8 • Courtemanche and He (2009) • Kumar et al. (1995) • Lin and Prince (2013) • McGarry et al. (2016) • Mellor (2000) • Schaber and Stum (2007) • Sloan and Norton (1997) (a) • Stum (2008)	14 • Bernet (2004) • Caro et al. (2011) • Chatterjee and Fan (2017) • Finkelstein and McGarry (2006) • Friedberg et al. (2017) • Gousia (2016) • Jiménez-Martín et al. (2016) • Konetzka and Luo (2011) • McCall et al. (1998) • McGarry et al. (2014) • McGarry et al. (2018) • McNamara and Lee (2004) • Mellor (2001) • Unruh et al. (2016) • Van Houtven et al. (2015)

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Table 2.C1 (continued)

Factor	Association		
	Negative	**None**	**Positive**
Number of children	**7**	**13**	**1**
Stated preferences	1 • Brau and Bruni (2008) (d)	3 • Costa-Font and Font (2009) (d) • Costa-Font and Rovira-Forns (2008)d • Wu et al. (2017)	0
Revealed preferences	6 • Cramer and Jensen (2006) • Gousia (2016) • Jiménez-Martín et al. (2016)d • McGarry et al. (2016) • McGarry et al. (2018) • Schaber and Stum (2007) (d)	10 • Barnett and Stum (2013)e • Browne and Zhou-Richter (2014) • Caro et al. (2011) • Friedberg et al. (2017) (e) • Konetzka and Luo (2011) • McGarry et al. (2014) • Mellor (2000) • Sloan and Norton (1997) • Van Houtven et al. (2015) • Zhou-Richter et al. (2010)	1 • Courbage and Roudaut (2008)
Married	**3**	**25**	**4**
Stated preferences	1 • Brau and Bruni (2008) (d)	5 • Allaire et al. (2016) • Costa-Font and Font (2009)d • Costa-Font and Rovira-Forns (2008)d • He and Chou (2020) • Wu et al. (2017)	0
Revealed preferences	2 • McNamara and Lee (2004) • Schaber and Stum (2007) (d)	20 • Browne and Zhou-Richter (2014) • Chatterjee and Fan (2017) • Courbage and Roudaut (2008) (e) • Courtemanche and He (2009) • Friedberg et al. (2017) • Gousia (2016) (e) • Jiménez-Martín et al. (2016) • Konetzka and Luo (2011) • Li and Jensen (2012) (f) • McCall et al. (1998) • McGarry et al. (2014) • McGarry et al. (2016) • McGarry et al. (2018) • Mellor (2000) • Mellor (2001) • Sloan and Norton (1997) • Stum (2008) • Swamy (2004) • Unruh et al. (2016) • Zhou-Richter et al. (2010)	4 • Bernet (2004) • Gottlieb and Mitchell (2015) • Kumar et al. (1995) • Van Houtven et al. (2015)
Bequest motive	**0**	**4**	**3**
Stated preferences	0	1 • He and Chou (2020)	0

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Table 2.C1 (continued)

Factor	Association		
	Negative	None	Positive
Revealed preferences	0	3 • Schaber and Stum (2007) • Sloan and Norton (1997) • Stum (2008)	3 • Boyer et al. (2017) • Brown, Goda and McGarry (2012) • Chatterjee and Fan (2017)
Subjective health	**2**	**19**	**10**
Stated preferences	0	4 • Ameriks et al. (2018) • Allaire et al. (2016) • Brau et al. (2010) • Costa-Font and Font (2009)	2 • Brau and Bruni (2008) • Costa-Font and Rovira-Forns (2008)
Revealed preferences	2 • Li and Jensen (2012) • Stum (2008)	15 • Barnett and Stum (2013) • Browne and Zhou-Richter (2014) • Caro et al. (2011) • Chatterjee and Fan (2017) • Courbage and Roudaut (2008) • Courtemanche and He (2009) • Friedberg et al. (2017) • Gottlieb and Mitchell (2015) • Gousia (2016) • Konetzka and Luo (2011) • McGarry et al. (2016) • McGarry et al. (2018) • Mellor (2000) • Schaber and Stum (2007) • Sloan and Norton (1997) (a)	8 • Bernet (2004) • Cramer and Jensen (2006) • McCall et al. (1998) • McGarry et al. (2014) • McNamara and Lee (2004) • Mellor (2001) • Unruh et al. (2016) • Van Houtven et al. (2015)
Subjective LTC risk	**0**	**5**	**14**
Stated preferences	0	3 • Ameriks et al. (2018) • Costa-Font and Font (2009) (g) • Wu et al. (2017) (h)	1 • He and Chou (2020)
Revealed preferences	0	2 • Friedberg et al. (2017) • Kumar et al. (1995) (h)	13 • Brown et al. (2012) • Caro et al. (2011) • Chatterjee and Fan (2017) • Costa-Font and Rovira-Forns (2008) • Finkelstein and McGarry (2006) • Gottlieb and Mitchell (2015) • Kitajima (1999) • McGarry et al. (2016) • McGarry et al. (2018) • Schaber and Stum (2007) • Sloan and Norton (1997) • Swamy (2004) • Unruh et al. (2016)
Subjective longevity	**0**	**6**	**0**
Stated preferences	0	3 • Costa-Font and Font (2009) (h) • Costa-Font and Rovira-Forns (2008) • Wu et al. (2017)	0

(continued on next page)

Table 2.C1 (continued)

Factor	Association		
	Negative	None	Positive
Revealed preferences	0	3 • Caro et al. (2011) • Cramer and Jensen (2006) • Sloan and Norton (1997)	0
ADL impairments	**1**	**14**	**3**
Stated preferences	0	1 • Ameriks et al. (2018)	1 • Kennedy et al. (2016)
Revealed preferences	1 • Konetzka and Luo (2011)	13 • Bernet (2004) • Caro et al. (2011) • Chatterjee and Fan (2017) • Courtemanche and He (2009) • Friedberg et al. (2017) • Gottlieb and Mitchell (2015) • Li and Jensen (2012) • McCall et al. (1998) • McGarry et al. (2016) • McGarry et al. (2018) • Mellor (2000) • Mellor (2001) • Sloan and Norton (1997)	2 • Courbage and Roudaut (2008) • Nixon (2014)
Risk aversion	**2**	**3**	**2**
Stated preferences	0	1 • Costa-Font and Rovira-Forns (2008)	0
Revealed preferences	2 • Boyer et al. (2017) • Gousia (2016)	2 • Gottlieb and Mitchell (2015) • Sloan and Norton (1997)	2 • Chatterjee and Fan (2017) • Stum (2008)
Preference for formal care	**0**	**0**	**3**
Stated preferences	0	0	1 • He and Chou (2020)
Revealed preferences	0	0	2 • Boyer et al. (2017) • Brown et al. (2012)
Trust insurer	**0**	**0**	**2**
Stated preferences	0	0	0
Revealed preferences	0	0	2 • Brown et al. (2012) • Curry, Robison, Shugrue, Keenan and Kapp (2009)
Financial literacy	**1**	**0**	**4**
Stated preferences	0	0	1 • He and Chou (2020)

(continued on next page)

Table 2.C1 (continued)

Factor	Association		
	Negative	**None**	**Positive**
Revealed preferences	1 • Boyer et al. (2017)	0	3 • Gousia (2016) • McGarry et al. (2016) • McGarry et al. (2018)
System knowledge	**0**	**4**	**1**
Stated preferences	0	0	1 • Kitajima (1999)
Revealed preferences	0	4 • Boyer et al. (2017) • Schaber and Stum (2007) • Swamy (2004) • Unruh et al. (2016)	0
Cognitive intactness	**0**	**3**	**1**
Stated preferences	0	0	0
Revealed preferences	0	3 • Gottlieb and Mitchell (2015) • McGarry et al. (2016) • Sloan and Norton (1997)	1 • Friedberg et al. (2017)
Awareness	**0**	**3**	**5**
Stated preferences	0	1 • Allaire et al. (2016)	0
Revealed preferences	0	2 • Barnett and Stum (2013) • Browne and Zhou-Richter (2014)	5 • Boyer et al. (2017) • Schaber and Stum (2007) • Stum (2008) • Swamy (2004) • Zhou-Richter et al. (2010)
LTC experience	**2**	**9**	**8**
Stated preferences	1 • Kitajima (1999)	2 • Allaire et al. (2016) • Wu et al. (2017)	3 • Brau &and Bruni (2008) • Kennedy et al. (2016) • Tennyson &and Yang (2014)
Revealed preferences	1 • Kumar et al. (1995)	7 • Barnett &and Stum (2013) • Coe, Skira and Van Houtven (2015) (i) • Cramer &and Jensen (2006) • Li &and Jensen (2012) (i) • Schaber &and Stum (2007) • Swamy (2004) • Unruh et al. (2016) (i)	5 • Courbage &and Roudaut (2008) • Jiménez-Martín et al. (2016) • Konetzka &and Luo (2011) • McCall et al. (1998) • Stum (2008)

Notes: (a) Reports different associations in equivalent analyses and is therefore counted under "none". (b) Reports two different age associations and is therefore counted under "none". (c) Reports different associations for "black", "Hispanic" and/or "other" and is therefore counted under "none". (d) Reports household size and is therefore counted under both children and married. (e) Reports having children (or not) rather than number of children. (f) Reports different associations for married individuals compared to individuals that are single, divorced or widowed and is therefore counted under "none". (g) Reports an interaction of LTC risk and longevity risk. (h) Reports different associations for home care and nursing home expectations and is therefore counted under "none".(i) Reports different associations for different proxies of LTC experience and is therefore counted under "none".

Table 2.C2 Overview of findings by studies on individual factors associated with LTCI uptake

Factor	Association		
	Negative	**None**	**Positive**
Social benefits	**4**	**6**	**0**
Stated preferences	0	1 • He and Chou (2020)	0
Revealed preferences	4 • Brown, Coe and Finkelstein (2007) (a) • Doerpinghaus and Gustavson (2002) • Jiménez-Martín et al. (2016) • Konetzka and Luo (2011)	5 • Kumar et al. (1995) (b) • Li and Jensen (2012) • McGarry et al. (2018) • Sloan and Norton (1997) (c) • Stevenson et al. (2009) (b)	0
Tax incentive	**0**	**4**	**5**
Stated preferences	0	0	0
Revealed preferences	0	4 • McGarry et al. (2018) • Nixon (2014) • Stevenson et al. (2009) (d) • Stum (2008)	5 • Cornell and Grabowski (2018) (a) • Cramer and Jensen (2006)Courtemanche and He (2009) (a) • Goda (2011) (a) • Jiménez-Martín et al. (2016)
Informal care availability	**4**	**7**	**2**
Stated preferences	0	3 • Ameriks et al. (2018) • He and Chou (2020) • Wu et al. (2017)	0
Revealed preferences	4 • Bernet (2004) • Brown et al. (2012) • McCall et al. (1998) • McGarry et al. (2018)	4 • McGarry et al. (2016) • Mellor (2001) • Schaber and Stum (2007) • Stum (2008)	2 • Boyer et al. (2017) • Coe et al. (2015)

Notes: (a) Quasi-experimental study (highest level of evidence available). (b) Reports different associations of various measures of social benefit generosity and is therefore counted under "none". (c) Reports different associations in equivalent analyses and is therefore counted under "none". (d) Reports different associations of tax deductions and tax credits and is therefore counted under "none".

D. Individual and contextual level empirical evidence on annuity uptake

Table 2.D1 Overview of findings per study on individual factors associated with annuity uptake

Factor	Association		
	Negative	**None**	**Positive**
Being female	**4**	**12**	**7**
Stated preferences	2 • Nosi, D'Agostino, Pagliuca and Pratesi (2017) • Teppa (2011)	7 • Bateman et al. (2017) • Beshears, Choi, Laibson, Madrian and Zeldes (2014) • Bockweg, Ponds, Steenbeek and Vonken (2016) • Cappelletti, Guazzarotti and Tommasino (2013) • Chou, Inkmann, Van Kippersluis and Chan (2016) • Pfarr and Schneider (2013) • Shu, Zeithammer and Payne (2018)	1 • Guillemette, Martin, Cummings and James (2016)
Revealed preferences	2 • Bütler and Teppa (2007) • Inkmann, Lopes and Michaelides (2011)	5 • Hagen (2015) (a) • Hurd and Panis (2006) • Hurwitz and Sade (2017) • Schreiber and Weber (2016) • Ziegelmeyer and Nick (2013)	6 • Benartzi, Previtero and Thaler (2011) • Brown and Previtero (2014) • Chalmers and Reuter (2012) • Clark, Morrill and Vanderweide (2014) • Lee (2016) • Previtero (2014)
Age	**8**	**7**	**7**
Stated preferences	4 • Brown, Kapteyn, Luttmer and Mitchell (2017) • Guillemette et al. (2016) • Schooley-Pettis and Worden (2013) • Schreiber and Weber (2016)	3 • Beshears et al. (2014) • Shu et al. (2018) • Teppa (2011)	4 • Bockweg et al. (2016) • Cappelletti et al. (2013) • Chou et al. (2016) • Van der Cruijsen and Jonker (2016)
Revealed preferences	4 • Bernheim (1991) • Clark et al. (2014) • Hurd and Panis (2006) • Hurwitz and Sade (2017)	4 • Inkmann et al. (2011) • Pfarr and Schneider (2013) • Previtero (2014) (a) • Ziegelmeyer and Nick (2013)	3 • Benartzi et al. (2011) • Brown and Previtero (2014) • Lee (2016)
Non-white	**0**	**1**	**1**
Stated preferences	0	0	0
Revealed preferences	0	1 • Brown (2001)	1 • Hurd and Panis (2006)
Education	**0**	**14**	**3**

(continued on next page)

Table 2.D1 (continued)

Factor	Association		
	Negative	None	Positive
Stated preferences	0	8 • Beshears et al. (2014) • Cappelletti et al. (2013) • Chou et al. (2016) • Guillemette et al. (2016) • Nosi et al. (2017) • Schooley-Pettis and Worden (2013) • Schreiber and Weber (2016) • Van der Cruijsen and Jonker (2016)	2 • Bateman et al. (2017) • Brown, Kapteyn, Luttmer and Mitchell (2017)
Revealed preferences	0	6 • Brown (2001) • Hagen (2015) • Hurd and Panis (2006) • Pfarr and Schneider (2013) • Previtero (2014) (a) • Ziegelmeyer and Nick (2013)	1 • Inkmann et al. (2011)
Income	**1**	**9**	**4**
Stated preferences	0	8 • Bockweg et al. (2016) • Cappelletti et al. (2013) • Chou et al. (2016) • Guillemette et al. (2016) • Nosi et al. (2017) • Schreiber and Weber (2016) • Shu et al. (2018) • Van der Cruijsen and Jonker (2016)	0
Revealed preferences	1 • Previtero (2014)	1 • Ziegelmeyer and Nick (2013)	4 • Chalmers and Reuter (2012) • Clark et al. (2014) • Hagen (2015) • Pfarr and Schneide (2013)
Home ownership	**0**	**4**	**0**
Stated preferences	0	2 • Beshears et al. (2014) • Van der Cruijsen and Jonker (2016)	0
Revealed preferences	0	2 • Pfarr and Schneider (2013) • Ziegelmeyer and Nick (2013)	0
Wealth	**1**	**5**	**9**
Stated preferences	0	5 • Bateman et al. (2017) • Chou et al. (2016) • Guillemette et al. (2016) • Shu et al. (2018) • Van der Cruijsen and Jonker (2016)	2 • Bockweg et al. (2016) • Cappelletti et al. (2013)

(continued on next page)

Table 2.D1 (continued)

Factor	Association		
	Negative	**None**	**Positive**
Revealed preferences	1 • Brown (2001)	0	7 • Bernheim (1991) • Bütler, Staubli and Zito (2013) • Bütler and Teppa (2007) • Hurd and Panis (2006) • Inkmann et al. (2011) • Knoller, Kraut and Schoenmaekers (2016) • Ziegelmeyer and Nick (2013)
Children	**1**	**12**	**0**
Stated preferences	1 • Schreiber and Weber (2016)	6 • Beshears et al. (2014) • Bockweg et al. (2016) • Cappelletti et al. (2013) • Chou et al. (2016) • Shu et al. (2018) (b) • Van der Cruijsen and Jonker (2016)b	0
Revealed preferences	0	6 • Bernheim (1991) (b) • Bütler and Teppa (2007) • Hagen (2015) (b) • Inkmann et al. (2011) • Pfarr and Schneider (2013) • Ziegelmeyer and Nick (2013)	0
Married	**2**	**15**	**0**
Stated preferences	0	9 • Bateman et al. (2017) • Beshears et al. (2014) • Bockweg et al. (2016) • Cappelletti et al. (2013) • Chou et al. (2016) (c) • Guillemette et al. (2016) • Schooley-Pettis and Worden (2013) • Schreiber and Weber (2016) • Shu et al. (2018)	0
Revealed preferences	2 • Brown (2001) • Inkmann et al. (2011)	6 • Bernheim (1991) (c) • Bütler and Teppa (2007) (c) • Hagen (2015) (a) • Hurwitz and Sade (2017) • Pfarr and Schneider (2013) • Ziegelmeyer and Nick (2013)	0
Bequest motive	**1**	**5**	**1**
Stated preferences	1 • Bateman et al. (2017)	4 • Schooley-Pettis and Worden (2013) • Shu et al. (2018) • Teppa (2011) • Van der Cruijsen and Jonker (2016)	1 • Chou et al. (2016)

(continued on next page)

Table 2.D1 (continued)

Factor	Association		
	Negative	None	Positive
Revealed preferences	0	1 • Brown (2001)	0
Subjective health	**0**	**6**	**3**
Stated preferences	0	5 • Cappelletti et al. (2013) • Chou et al. (2016) • Schooley-Pettis and Worden (2013) • Shu et al. (2018) • Van der Cruijsen and Jonker (2016)	1 • Bockweg et al. (2016)
Revealed preferences	0	1 • Wuppermann (2017)	2 • Hurd and Panis (2006) • Brown (2001)
Subjective longevity	**1**	**7**	**4**
Stated preferences	1 • Chou et al. (2016)	3 • Bateman et al. (2017) • Bockweg et al. (2016) • Shu et al. (2018)	4 • Payne, Sagara, Shu, Appelt and Johnson (2013) • Schreiber and Weber (2016) • Teppa (2011) • Van der Cruijsen and Jonker (2016)
Revealed preferences	0	4 • Hurd and Panis (2006) • Inkmann et al. (2011) • Pfarr and Schneider (2013) • Brown (2001)	0
Objective longevity	**0**	**2**	**2**
Stated preferences	0	0	0
Revealed preferences	0	2 • Hurwitz and Sade (2017) (d, e) • Wuppermann (2017) (f)	2 • Chalmers and Reuter (2012) (f) • Lee (2016) (d)
Risk aversion	**3**	**5**	**3**
Stated preferences	3 • Guillemette et al. (2016) • Knoller (2016) • Shu et al. (2018)	4 • Agnew et al. (2008)a • Cappelletti et al. (2013) • Chou et al. (2016) • Schreiber and Weber (2016)	3 • Bockweg et al. (2016) • Schooley-Pettis and Worden (2013) • Van der Cruijsen and Jonker (2016)
Revealed preferences	0	1 • Pfarr and Schneider (2013)	0

(continued on next page)

Table 2.D1 (continued)

Factor	Association		
	Negative	None	Positive
Stock market participation	**1**	**3**	**2**
Stated preferences	1 • Cappelletti et al. (2013)	2 • Chou et al. (2016) • Guillemette et al. (2016)	1 • Bockweg et al. (2016)
Revealed preferences	0	1 • Inkmann et al. (2011)	1 • Pfarr and Schneider (2013
Patience	**0**	**0**	**4**
Stated preferences	0	0	3 • Bockweg et al. (2016) • Cappelletti et al. (2013) • Van der Cruijsen and Jonker (2016)
Revealed preferences	0	0	1 • Brown (2001)
Trust in insurers	**0**	**1**	**1**
Stated preferences	0	1 • Bockweg et al. (2016)	1 • Van der Cruijsen and Jonker (2016)
Revealed preferences	0	0	0
Financial literacy	**2**	**4**	**4**
Stated preferences	2 • Agnew, Anderson, Gerlach and Szykman (2008) • Chou et al. (2016)	4 • Bateman et al. (2017) • Bockweg et al. (2016) • Cappelletti et al. (2013) (g) • Shu et al. (2018)	3 • Ai, Brockett, Golden and Zhu (2017) • Brown, Kapteyn, Luttmer and Mitchell (2017) • Schreiber and Weber (2016)
Revealed preferences	0	0	1 • Ziegelmeyer and Nick (2013)
Awareness	**0**	**0**	**2**
Stated preferences	0	0	2 • Ai et al. (2017) • Brown, Kapteyn, Luttmer, Mitchell and Samek (2017)
Revealed preferences	0	0	0

Notes: (a) Reports different associations in equivalent analyses and is therefore counted under "none". (b) Reports having children (or not) rather than number of children. (c) Reports different association sfor married individuals compared to individuals that are single, divorced or widowed and is therefore counted under "none". (d) Reports ex-ante mortality. (e) Reports different associations for two measures of ex-ante mortality and is therefore counted under "none". (f) Reports ex-post mortality. (g) Reports different associations for three different measures of financial literacy and is therefore counted under "none".

Table 2.D2 Overview of findings by studies on contextual factors associated with annuity uptake

Factor	Association: Negative	Association: None	Association: Positive
Social benefits	**1**	**2**	**0**
Stated preferences	0	2 • Chou et al. (2016) (a) • Schreiber and Weber (2016)	0
Revealed preferences	1 • Bernheim (1991)	0	0
Tax incentive	**0**	**0**	**3**
Stated preferences	0	0	0
Revealed preferences	0	0	3 • Hagen (2015) • Lee (2016) • Pfarr and Schneider (2013)
Annuity equivalent worth	**1**	**0**	**5**
Stated preferences	0	0	0
Revealed preferences	1 • Chalmers and Reuter (2012)	0	5 • Brown (2001) • Bütler et al. (2013) (b) • Bütler and Teppa (2007) • Clark et al. (2014) (c) • Lee (2016)
Return on investments	**3**	**1**	**0**
Stated preferences	0	0	0
Revealed preferences	3 • Brown and Previtero (2014) • Chalmers and Reuter (2012) • Previtero (2014)	1 • Lee (2016)	0
Annuity as default	**0**	**1**	**4**
Stated preferences	0	1 • Agnew et al. (2008)	2 • Bateman et al. (2017) • Bockweg et al. (2016)
Revealed preferences	0	0	2 • Bütler et al. (2013) • Bütler and Teppa (2007)

(continued on next page)

Table 2.D2 (continued)

Factor	Association		
	Negative	None	Positive
Framing as investment	**4**	**1**	**0**
Stated preferences	• 3 • Bockweg et al. (2016) (b, d) • Brown, Kling, Mullainathan and Wrobel (2013) • Guillemette et al. (2016)	• 1 • Beshears et al. (2014) (b)	0
Revealed preferences	• 1 • Benartzi et al. (2011)	0	0
Protections	**0**	**1**	**4**
Stated preferences	0	1 • Chou et al. (2016) (e)	3 • Brown et al. (2013) (f) • Knoller (2016) (b, f) • Lee (2016) (g)
Revealed preferences	0	0	1 • Knoller et al. (2016) (f)

Notes: (a) Reports different associations for different social benefit schemes and is therefore counted under "none". (b) Quasi-experimental study (highest level of evidence available). (c) Reports a lump sum value rather than annuity equivalent worth. (d) Reports a negative association with framing annuities as investment with potential loss, but not with framing annuities as investment with potential gain. (e) Reports a positive association of period guarantees and a negative association of inflation protection and is therefore counted under "none". (f) Reports the association with principal protection or guarantees. (g) Reports the association with fixed interest rates.

4

Ambiguous nonperformance risks

An important societal problem is that people underinsure against risks that are unlikely or occur in the far future, such as natural disasters and long-term care needs. One explanation is that uncertainty about the risk of non-reimbursement induces ambiguity averse and risk prudent decision makers to take out less insurance. We set up an insurance experiment to test this explanation. Consistent with the theoretical predictions, we find that the demand for insurance is lower when the nonperformance risk is ambiguous than when it is known and when decision makers are risk prudent. We cannot attribute the lower take-up of insurance to our measure of ambiguity aversion, probably because ambiguity attitudes are richer than aversion alone.

Based on:
"Insurance decisions under nonperformance risk and ambiguity"

with Paul van Bruggen and Han Bleichrodt
in the Journal of Risk and Uncertainty, 63(3), 229-253.

4. Ambiguous nonperformance risks

4.1. Introduction

The motivation for this paper is an important puzzle in insurance economics: why do people take out too little insurance against risks with potential huge consequences, such as natural disasters and long-term care needs. Standard insurance theory suggests that such insurance should be valuable as it protects individuals against the potentially devastating costs of these events. In practice, however, the holding of such insurance is (too) low.[57] Although various reasons have been put forward to explain this puzzle, it is still only partially understood. A better understanding is important for policy, as it may protect people from financial distress and governments from footing the bill.

One possible reason is that people are concerned that insurers will not pay out future claims. This is not unheard of. For example, after Hurricane Katrina, insurers denied coverage to people who had home insurance, but no additional flood coverage (Kunreuther & Pauly 2006). During the COVID-19 pandemic, insurers across the globe have been hesitant to pay out claims for business interruption insurance and there is a fair amount of ongoing litigation about whether lost business income due to lockdowns is covered or not. Concerns about such nonperformance may be particularly grave when benefits occur in the far future, which carries the risk that insurers may go bankrupt, and which makes the value of insurance inherently more risky and ambiguous.[58] [59] The purpose of this paper is to explore the role of ambiguity regarding nonperformance on insurance take-up. We consider the case of full insurance. Because full insurance is equivalent to what Ehrlich and Becker (1972) call self-protection, our results also help to better understand underinvestment in prevention.

Multiple theoretical predictions relevant to insurance with nonperformance risk pointed to the importance of (higher order) risk and ambiguity attitudes in explaining behavior.[60] While the effect of risk aversion is equivocal (Dionne & Eeckhoudt 1985), Peter and Ying (2020) show that ambiguity averse decision makers will reduce their demand for insurance when the nonperformance risk is ambiguous. Moreover, developments in the domain of higher order risk preferences, which relate to how people prefer to combine risks, suggest that risk prudence has an important effect: it decreases the demand for insurance with nonperformance risk (Eeckhoudt & Gollier 2005). These theoretical predictions have, however, received little attention in the empirical literature.

We set up an experiment and relate uptake decisions for full insurance to both ambiguity and (higher order) risk and ambiguity preferences. Our main finding is that ambiguity of the nonperformance risk indeed decreases the demand for insurance. Risk attitudes are important in explaining insurance behavior: risk aversion increases insurance demand, while risk prudence, as predicted, affects it negatively. We could not link the observed insurance behavior to our measure of ambiguity aversion. The reason was that the ambiguity attitudes we observed were richer than aversion alone: for more likely events our subjects were predominantly ambiguity loving (remember that insurance decisions involve losses). The main factor influencing insurance demand is the size of the insurable risk. The larger this probability is, the more likely our subjects were to demand insurance. While our findings on ambiguity attitudes are consistent with prospect theory, the findings on the role of the loss probability are not. They pose a challenge to prospect theory.

This chapter proceeds as follows. Section 4.2 provides a review of the literature. Section 4.3 presents our experiment design. Section 4.4 presents our empirical findings. Implications of which are discussed in Section 4.5. Section 4.6 concludes.

57 See Kunreuther (1996) and Pestieau and Ponthière (2012) for a discussion of these respective underinsurance puzzles.
58 Li, Neumuller and Rothschild (2021) make a similar point and observe that insolvency risk of insurers increases over time.
59 Although state guaranty associations exist in the US to protect against the insolvency of insurers, some states do not allow to advertise this fact, and many consumers are unaware of their existence.
60 Most predictions have been made in the context of self-protection. Given the equivalence to full insurance with nonperformance risk, we refer to these as insurance predictions throughout.

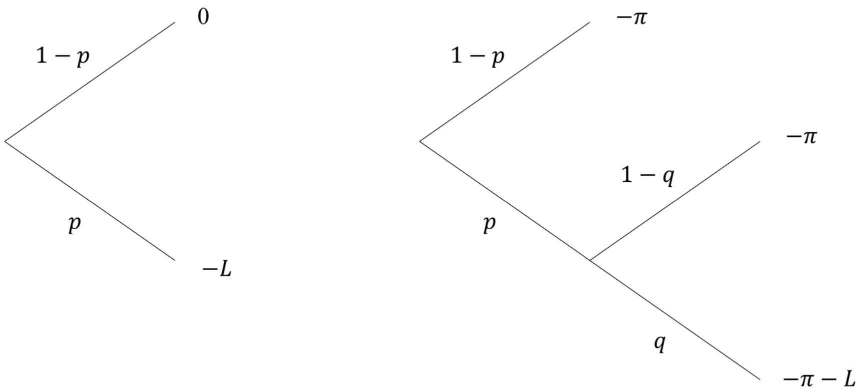
4.2. Background

4.2.1. Theory

Consider a standard full insurance policy. This theoretical product fully reimburses a loss L occurring with probability p (the *insurable risk*) and is available at an actuarially fair premium $\pi = pL$. In practice, however, insurance has a probability of nonperformance with which insurers do not pay out a valid claim. Nonperformance may occur for various reasons, one of which is that that benefits occur in the far future and the insurance company may no longer exist.

If there is a risk of nonperformance , buying insurance no longer eliminates the insurable risk, but reduces it from p to $pq > 0$. In our experiment, p and q may or may not be objectively known. If either p or q is unknown (or if both are), the decision is made under ambiguity. An individual's choice whether to buy insurance can be schematically depicted as in Figure 4.1. In the special case of full insurance, insurance with nonperformance risk is equivalent to Ehrlich and Becker's (1972) concept of self-protection (also called prevention): both reduce the risk of incurring a loss, but they do not completely remove it.[61] Hence, while part of the literature that we discuss below is framed as prevention, their results are equally applicable to insurance decisions with a risk of nonperformance in the special case of full insurance. One caveat that should be made here is that in Figure 4.1 the choice is binary: either insurance or no insurance. Most of the literature on self-protection is about the level of effort. Denuit et al. (2016) show, however, that the same difficulties that have been identified to choice of the optimal level of self-protection apply to the binary choice between two levels of self-protection.

Figure 4.1 The insurance choice: no insurance (left) versus insurance with nonperformance risk (right)



The literature has identified several factors that affect demand for insurance with nonperformance risk. The first contributions focused on the role of risk aversion, taking q, the probability of nonperformance, as known. Dionne and Eeckhoudt (1985) show that for expected utility maximizers with a quadratic utility function, risk aversion increases (decreases) the uptake of insurance with nonperformance risk when $p < 0.5$ $(p > 0.5)$. This result arises because the insurance itself is risky; purchasing it deteriorates the worst possible outcome with the insurance premium paid (Bryis & Schlesinger 1990).[62] Jullien, Salanié and Salanié (1999) extend Dionne and Eeckhoudt's (1985) analysis to more general utility functions. They derive that in general the effect of risk aversion on insurance uptake is also inverse U-shaped: risk aversion increases insurance uptake up to some endogenous threshold of p, which depends on the utility functions of both agents under comparison, and then decreases it.[63]

61 Buying insurance at premium $\pi = p(1 - q)L$ is then a risk reducing activity equivalent to exerting preventive effort.

62 Doherty and Schlesinger (1990) show that a similar argument applies to partial insurance with a nonperformance risk, rendering the effect of risk aversion on insurance demand indeterminate.

63 Peter (2020) finds qualitatively similar results for an exogenous threshold that depends only on the utility of the benchmark agent.

Eeckhoudt and Gollier (2005) show that higher order risk attitudes also affect the demand for insurance. In particular, they prove that, compared with the risk-neutral benchmark, risk prudence reduces the demand for insurance. Peter (2020) shows that this also holds when the benchmark agents has more general risk preferences. Risk prudence implies an aversion to downside risk or to combining bad events with bad events (Eeckhoudt & Schlesinger 2006). Buying insurance with nonperformance risk entails more downside risk, as two bad events can occur simultaneously: paying the premium, while also incurring the loss. This makes such insurance unattractive to risk prudent individuals. Menegatti (2009) and Peter (2017) extend these findings to an intertemporal model where the decision maker pays an insurance premium now to cover a future loss in the presence of nonperformance risk. Courbage and Rey (2006) extend the analysis of the effect of prudence on insurance to decisions involving both health and wealth. They show that individuals who lose more from being sick will demand more insurance, provided that they are less prudent about wealth.

The above analyses are based on expected utility. Baillon, Bleichrodt, Emirmahmutoglu, Jaspersen and Peter (2020) consider rank-dependent utility (prospect theory for losses) and derive the implications of probability weighting on prevention, which, as we noted above, is equivalent to full insurance with nonperformance risk. They show that for intermediate probabilities, inverse S-shaped probability weighting, the most commonly observed case, will lead to underinsurance.

Finally, Snow (2011) and Peter and Ying (2020) study the impact of ambiguity aversion when the insurance decision is made under ambiguity. They both assume that the decision maker is risk and ambiguity averse. This assumption is not uncontroversial as people tend to be ambiguity seeking for unlikely events and losses (Kocher, Lahno & Trautmann 2018), which typically occur in insurance decisions. Peter and Ying (2020) show that an ambiguous nonperformance risk always reduces the demand for insurance (compared with a known nonperformance risk), regardless of whether the insurable risk is ambiguous or not. Snow (2011) shows that an ambiguous insurable risk increases the demand for insurance in the presence of a known nonperformance risk.[64] This happens because insurance reduces the ambiguity of the insurable risk and an ambiguity averse decision maker likes reductions in ambiguity.[65]

Table 4.1 summarizes the various cases. The first letter indicates whether the insurable risk (p) is known (K) or unknown (U) and the second letter whether the nonperformance risk (q) is known (K) or unknown (U). A + (-) sign indicates that insurance demand is higher (lower) for the row combination than for the column combination. A question mark indicates that this case has not yet been explored in the literature. Combining the results of Peter and Ying (2020) and Snow (2011), Table 4.1 shows that the demand for insurance must be higher when the insurable risk is unknown and the nonperformance risk is known than when the insurable risk is known and the nonperformance risk is unknown: in the first case, insurance reduces ambiguity, whereas in the latter case, it increases it.[66]

Table 4.1 Relative attractiveness of insurance with nonperformance risk under risk and ambiguity (row vs column)

Treatment	*KK*	*KU*	*UK*
KU	- (a)		
UK	+ (b)	+ (c)	
UU	?	?	- (a)

Notes: Treatments *KK*, *KU*, *UK* and *UU* indicate whether the insurable risk (p) and nonperformance risk (q) respectively are known (K) or unknown (U). Superscripts indicate whether the prediction is derived from (a) Peter and Ying (2020), (b) Snow (2011) or (c) inferred from both.

64 Viscusi (1979) already noted that a more precise (i.e., less ambiguous) probability assessment conversely reduces insurance demand.

65 Alary, Gollier, and Treich (2013) derive the opposite prediction when assuming that insuring (in their paper self-protection) increases the ambiguity of the insurable risk. When insuring does not affect ambiguity, ambiguity aversion may either decrease or increase insurance demand. Snow's (2011) assumption is more natural for our context, and matches our experimental implementation, hence we follow his prediction.

66 Denoting the demand for insurance given treatment t as $D(t)$, if $D(UK) > D(KK)$, which is what Snow (2011) shows, and $D(KK) > D(KU)$, which is what Peter and Ying (2020) show, then it logically follows that $D(UK) > D(KU)$.

The impact of higher order ambiguity preferences has hardly been explored. This is partly because they were defined only recently (Baillon 2017). Peter and Ying (2020) derive that more ambiguity leads to less insurance demand provided that ambiguity prudence is not too large.

4.2.2. Empirical evidence

Several studies have shown that the introduction of a known nonperformance risk decreases the demand for full insurance (Herrero, Tomás & Villar 2006; Wakker, Thaler & Tversky 1997; Zimmer, Gründl, Schade & Glenzer 2018; Zimmer, Schade & Gründl 2009). Bajtelsmit, Coats and Thistle (2015) show that this also holds when the nonperformance risk is ambiguous. Biener, Landman and Santana (2019) find tentative evidence that an ambiguous nonperformance risk may reduce insurance demand compared to a known one. This is an empirical matter that we will further address in our current study.

Krieger and Mayrhofer (2017) and Masuda and Lee (2019) investigate the role of higher-order risk preferences in prevention decisions. Krieger and Mayrhofer (2017) find that more prudent decision makers invest less in prevention, which is consistent with the predictions of Eeckhoudt and Gollier (2005). Masuda and Lee (2019) also find that their subjects exert too little preventive effort regardless of the timing of the loss. They argue that their results cannot be explained by expected utility and suggest probability weighting as an alternative explanation, in line with the analysis of Baillon, Bleichrodt, Emirmahmutoglu, Jaspersen and Peter (2020).

4.3. Experiment

The purpose of our paper is twofold. First, we empirically test the theoretical predictions in Table 4.1 and provide a complete picture of the effects of unknown insurable and nonperformance risks on the demand for insurance. Second, we explore whether the demand for insurance can be related to risk aversion and prudence and, in the cases where the risks are unknown, to ambiguity aversion and prudence. We therefore consider both known and unknown insurable risk and nonperformance risk: we consider each of the four cases *KK* (both the probability of the insurable loss and the probability of nonperformance are known), *KU*, *UK*, and *UU*.

4.3.1. Subjects

117 students from Erasmus University Rotterdam participated in the experiment, which was conducted at the Erasmus Behavioural Lab (EBL). There were 12 sessions with a maximum of 12 participants per session. Participants were seated in cubicles to avoid interaction. They were recruited from the subject pool of the EBL and they were instructed that the experiment could last up to 1 hour and 15 minutes. Participants were told that their expected payoff from the experiment was €25 with a minimum of €3.40 and a maximum of €134.20. Before starting the experiment, participants received €25 in cash. They were told that the experiment involved both the possibility of losing money and the possibility of gaining money and that they could pay eventual losses out of the €25. In this way, participants were stimulated to think of the average €25 payment as a reference point. The average payment per participant turned out to be €23.90.

4.3.2. Incentives

The experiment was incentivized using the PRINCE incentive system (Johnson, Baillon, Bleichrodt, Li, van Dolder & Wakker 2021), which has the advantage of making incentive compatibility transparent to the participants. The main property of PRINCE is that the choice to be played out for real is chosen upfront. In our study, prior to the experiment, participants were asked to pick any of 92 sealed envelopes representing the 92 choice tasks in the experiment. The participants took their selected envelope to their cubicle, making it clear that their answers could not affect the selection of the task that they would play out for real. They were not allowed to open their envelope until they returned to the instruction room after the experiment. The experiment choices were framed as instructions to the experimenters: for all 92 choice tasks participants were asked: "If your envelope contains this choice, which option would you like us to play out for real?" The choice tasks that the envelope contained described the entire choice task (that is, both options from a given task). The option that was played out for real was the one chosen by the participant in that choice task.

4.3.3. Experiment design

The experiment consisted of two parts, one measuring the demand for insurance with nonperformance risk, the other measuring participants' attitudes towards risk and ambiguity. In total, the experiment consisted of 92 binary choices: 56 choices measuring the demand for insurance, 32 choices measuring risk and ambiguity attitudes, and 4 choices that were repeated to test the quality of the data. A complete list of the choices is presented in Tables 4.A1-4.A6 in Appendix 4.A.

4.3.3.1. Insurance tasks

We used four treatments to measure the demand for insurance with nonperformance risk, which varied depending on whether the insurable risk and the nonperformance risk were known (*K*) or unknown (*U*). Thus, we studied all situations *KK*, *KU*, *UK* and *UU* listed in Table 4.1. There were 9 choices per treatment. In addition, we included five choices per treatment involving gains to make sure the expected payment from the experiment was €25. These choices are not used in the analyses.

Figure 4.2 shows an example of a choice from treatment *KK*, Figure 4.3 shows the counterpart from treatment *UU*. All choices were represented as situations where a token is drawn from a bag, possibly followed by a second draw from another bag. All bags contained 10 tokens. For risky choices, the tokens were colored (red and yellow or blue and orange as in Figure 4.2), for ambiguous choices, they had a question mark (see Figure 4.3). It was explained that the ambiguous bags contained 10 tokens with letters (A-J or Q-Z) in unknown proportion and that each letter could occur between 0 and 10 times. The bags were filled according to the instructions of a random person not affiliated with the experiment and participants were informed about this. To avoid suspicion, we asked each participant before the start of the incentivized choice tasks whether they wanted the letter A to be associated with the best outcome, the letter B with the second-best outcome etcetera, or whether they wanted the ranking to be reversed (such that A was associated with the worst outcome and Z with the best outcome).

Figure 4.2 and Figure 4.3 show that in the tasks measuring insurance demand, one option resembled no insurance and the other resembled insurance with a nonperformance risk. The no insurance option (we did not use this term in the experiment) involved a possible loss (€17.50 in Figure 4.2 and Figure 4.3). In the insurance option, subjects paid an actuarially fair premium (€1.40 in Figure 4.2 and Figure 4.3) to reduce the probability of the loss, but there was a nonperformance risk. This is depicted by the bag containing orange and blue tokens in Figure 4.2 and by the bag containing tokens with letters Q-Z in Figure 4.3. Note that we deliberately presented the insurance options as compound lotteries, to emphasize the differences in potential outcomes with the no insurance option.

Figure 4.2 Example of a choice task with known probabilities

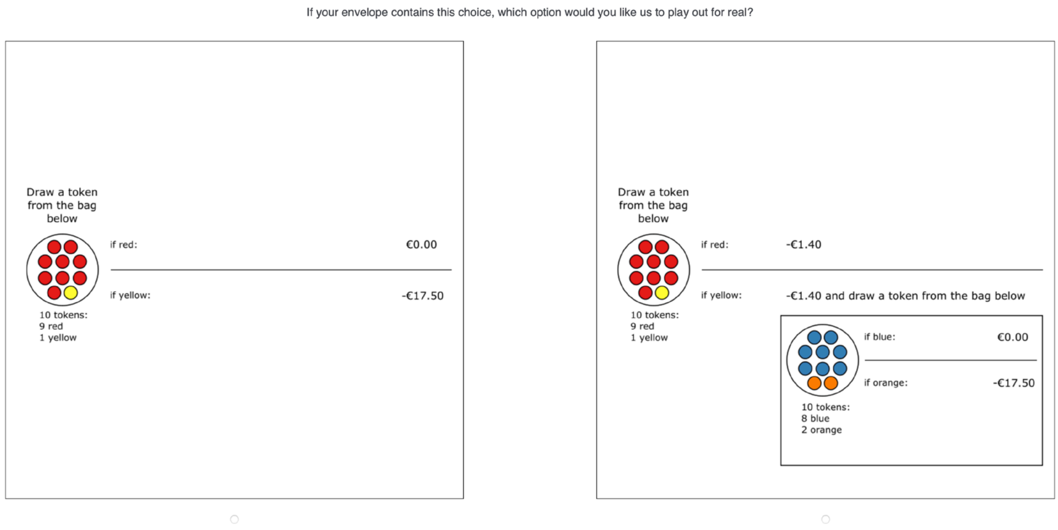
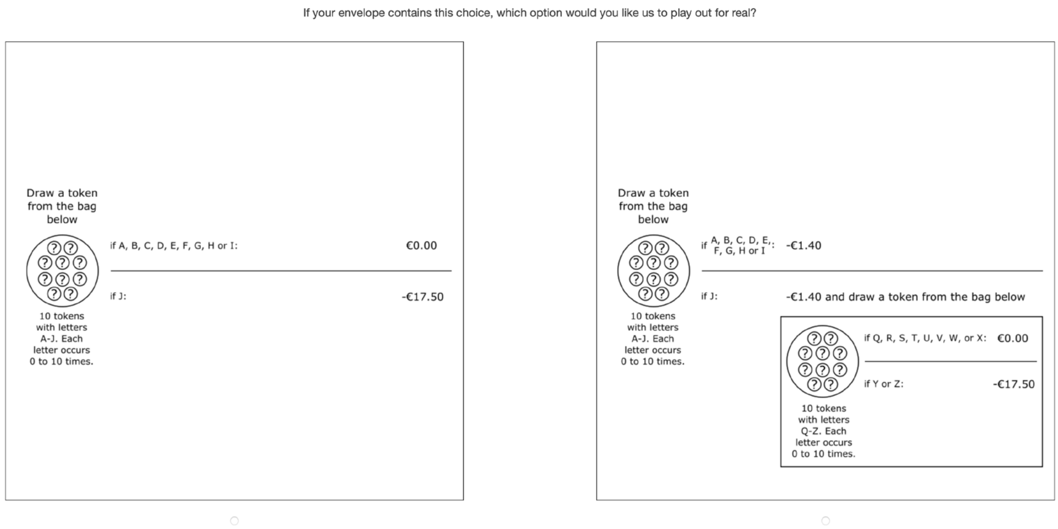


Figure 4.3 Example of a choice task with unknown probabilities



4.3.3.2. Risk and ambiguity attitudes

The second part measured risk aversion (9 choices), risk prudence (9 choices), ambiguity aversion (9 choices), and ambiguity prudence (5 choices). Figures 4.A1-4.A4 in Appendix 4.A give examples for each of these tasks. We used fewer choices to measure ambiguity prudence, because these questions were more complex and cognitively demanding. We developed these choice tasks to stay as close as possible to the insurance tasks. Hence, all tests involved only losses and €0. In addition, the risk and ambiguity prudence tasks were also presented in a compound form.[67]

A decision maker is risk averse when preferring a lottery over a mean-preserving spread of that lottery. To avoid the certainty effect, we chose to have both options risky. Then, risk aversion is defined as the preference:

$$(p : -k, 1-p : -r) \succsim (p : -k - \frac{1-p}{p} r, 1-p : 0)$$

for all $p \in [0,1]$ and k, $r > 0$. In the left lottery the harms -k and -r are disaggregated, i.e., only one of them occurs, while in the right lottery they are aggregated. In our experiment, p varied from 0.1 to 0.9 in steps of 0.1.

Eeckhoudt and Schlesinger (2006) define *risk prudence* as the preference of $(0.5: -k, 0.5: \tilde{\varepsilon})$ over $(0.5: -k + \tilde{\varepsilon}, 0.5: 0)$ for all $k > 0$ and for all zero mean random variables $\tilde{\varepsilon}$. This can be interpreted as a preference to disaggregate the two harms $-k$ and $\tilde{\varepsilon}$ over aggregating them.[68] The decision maker rather bears the loss in the state of the world where they do not bear the risk. In our experiment, $\tilde{\varepsilon}$ is a binary random variable with equiprobable outcomes s and $-s$. For each task, a sure amount c was deducted such that all possible outcomes were in the loss domain and choices could not be affected by loss aversion.

Where risk aversion and risk prudence are conditions about the spread of outcomes over different states, ambiguity aversion and ambiguity prudence are conditions about the spread in probabilities. Let $\tilde{\varepsilon}$ now denote a zero-mean nondegenerate random variable to which a probability p can be added such that $p + \tilde{\varepsilon} \in [0,1]$. The lotteries $(p: -k, 1 - p: 0)$ and $(p + \tilde{\varepsilon}: -k, 1 - p + \tilde{\varepsilon}: 0)$ then have the same expected probabilities of losing k, but for the first lottery this probability is known, while for the second lottery it is unknown. A decision maker is *ambiguity averse* if they prefer the lottery with known probabilities over the lottery with unknown probabilities:

$$(p : -k, 1-p : 0) \succsim (p + \tilde{\varepsilon} : -k, 1 - p - \tilde{\varepsilon} : 0)$$

for all zero mean random variables $\tilde{\varepsilon}$, for all $p + \tilde{\varepsilon} \in [0,1]$ and for all k.

Baillon (2017) defined the notion of ambiguity prudence. To define ambiguity prudence, we change the notation slightly. Let $(\{p, q + \tilde{\varepsilon}\}: -L)$ denote a lottery that determines with an unknown probability whether a loss of $L > 0$ is given with known probability p or with unknown probability $q + \tilde{\varepsilon}$ and else nothing happens (i.e., the outcome is 0). Now consider a given increase k in the probability of the loss L. Ambiguity prudence says that the decision maker will prefer to disaggregate these two harms. In other words, ambiguity prudent decision makers will prefer $(\{p + k, q + \tilde{\varepsilon}\}: -L)$ to $(\{p, q + \tilde{\varepsilon} + k\}: -L)$[69] As an example, we have $p = 0.5$, $q = 0.35$ and $k = 0.4$ in Figure 4.4.A4 in Appendix 4.A.

67 Prudence can depend on the presentation of lotteries. Recent studies found more prudence for compound lotteries than for reduced lotteries (Deck & Schlessinger 2018; Haering, Heinrich & Mayrhofer 2020).

68 Of course, the lottery $\tilde{\varepsilon}$ is only seen as harm if the decision maker is risk averse.

69 This definition implicitly assumes that all probabilities of a loss lie within the [0,1] interval.

Participants randomly started with the insurance part or with the risk and ambiguity part of the experiment. The order of the sub-parts within these parts and of the choice tasks within these sub-parts was also randomized.[70] The location (left or right) of any two options was randomized for each decision for each subject. After answering the incentivized choice tasks, participants were asked to answer four background questions. Two of these asked for subjects' gender and nationality (two of the main sources of variation in experimental samples). The other two were directly related to insurance uptake, asking subjects to indicate which insurance products (e.g., mobile phone insurance, legal aid insurance) they have and how large the voluntary deductible on their mandatory health insurance is.

Before the experiment, participants were given a generic instruction of the incentive structure in the instruction room (see Appendix 4.B1). Further instructions for the choice tasks were provided upon starting the experiment and are shown in Appendix 4.B2. After these instructions, participants answered four true-false questions to check their comprehension of the experiment. They could only proceed to the incentivized choice tasks once they had answered all comprehension questions correctly. In this way, participants received feedback on their understanding of the choice tasks. Additionally, summaries of the particularities of the choice tasks were given at the start of each sub-part and were followed by one true-false question. We ensured that an experimenter was available at all times to answer participants' questions.

After the experiment, participants were asked to return to the instruction room and choices were played out for real. A token was drawn for each of the possible bags used in the experiment. After drawing the tokens, participants could open their envelopes and the choice task it contained was recreated. Risky probabilities were played out by drawing colored tokens from a bag. For each probability p, a token was drawn from a bag with a total of 10 red or yellow tokens. The bags with colored tokens were filled while the participants were present so that they could check that the bags contained the correct number of red and yellow tokens. Then, a token was drawn 9 times; that is for all probabilities $0.1 \leq p \leq 0.9$ (Figure 4.2 shows $p = 0.1$). Similarly, for q, a token was drawn from a bag with a total of 10 blue or orange tokens in compositions representing $0.1 \leq q \leq 0.9$ (Figure 4.2 shows $q = 0.2$). Ambiguous probabilities were played out by drawing a token from a bag containing letters A-J (for p) and from a bag containing letters Q-Z (for q).

4.4. Results

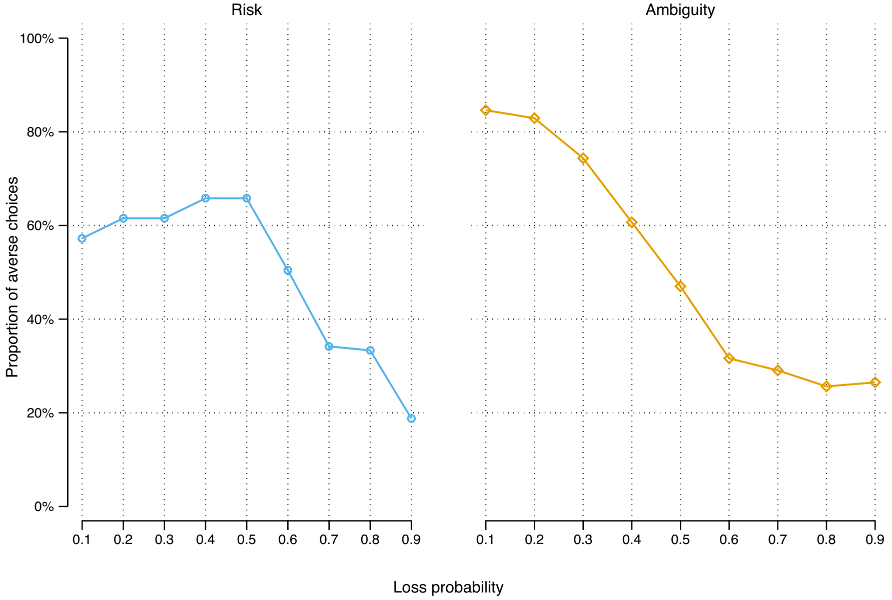
4.4.1. Risk and ambiguity attitudes

The theoretical results that we discussed in Section 4.2 show that risk and ambiguity attitudes play a central role in explaining insurance decisions with nonperformance risk. We, therefore, first present the results on risk aversion, risk prudence, ambiguity aversion, and ambiguity prudence before discussing our main result, the effect of ambiguity on the demand for insurance.

Figure 4.4 shows the proportion of risk and ambiguity averse choices split out by the loss probability. In the case of ambiguity, the displayed probability is the proportion of letters associated with the worst outcome. The figure shows evidence for the loss part of the fourfold pattern of risk and ambiguity aversion suggested by prospect theory: for small probabilities, subjects were mostly risk and ambiguity averse, for larger probabilities they were mostly risk and ambiguity seeking.

70 However, the ambiguity prudence sub-part was always last within the risk and ambiguity part of the experiment, because of the complexity of those choice tasks.

Figure 4.4 Proportion of risk averse and ambiguity averse choices for different loss probabilities



Overall, neither risk nor ambiguity aversion dominates. Bayesian tests provide strong support for the null that overall subjects are equally likely to choose the risky and the less risky option (Bayes factor[71] (*BF*) = 0.08) and support for the null that they are equally likely to choose the ambiguous and the unambiguous option (*BF* = 0.11). However, as we noted, this is driven by a consistent aggregate pattern of risk and ambiguity aversion for small loss probabilities and risk and ambiguity loving choices for medium and large loss probabilities. Bayesian testing shows support for the hypothesis that the proportion of risk averse choices is correlated with the loss probability (*BF* = 5.7) and very strong support for the hypothesis that the proportion of ambiguity averse choices is correlated with the loss probability (*BF* = 50.9).

Individual tests show support for risk aversion for probabilities less than 0.6 (all *BF* > 4.38 except for probability 0.1 for which the Bayesian test is inconclusive (*BF* = 0.72)), support for risk neutrality for probability 0.6 (*BF* = 0.23), and very strong support for risk seeking for probabilities exceeding 0.6 (all *BF* > 62.5). They also show very strong support for ambiguity aversion for probabilities less than 0.4 (all *BF* > 2.03×10^5, for probability 0.4 the test is inconclusive (*BF* = 2.86)), support for ambiguity neutrality for probability 0.5 (*BF* = 0.27), and very strong support for ambiguity seeking for probabilities exceeding 0.5 (all *BF* > 472.8).

We further investigate subjects' risk and ambiguity attitudes by classifying them into four different types: averse, loving, inverse S-shaped, and S-shaped. Inverse S-shaped is the assumption underlying prospect theory. It involves aversion for small probabilities of a loss but loving for large probabilities. S-shaped is the opposite, loving for small loss probabilities but aversion for large probabilities.

Subjects were classified as risk [ambiguity] averse if they chose the least risky [ambiguous] option at least twice both in the three tasks where the probability of a loss was at most 0.3 ('small probabilities') and in the three tasks where the probability was at least 0.7 ('large

71 The Bayes factor (*BF*) indicates how much more likely the alternative hypothesis is than the null. A *BF* larger than 3 is usually interpreted as providing some support for the alternative, a *BF* larger than 10 as providing strong support for the alternative, and a *BF* larger than 30 as providing very strong support for the alternative. Similarly a *BF* less than 0.33 is interpreted as providing some support for the null, less than 0.1 as providing strong support for the null, and less than 0.03 as providing very strong support for the null. *BF*s between 0.3 and 3 are interpreted as inconclusive evidence.

probabilities'). They were classified as risk [ambiguity] loving if they chose the most risky [ambiguous] option at least twice in both the small and the large probability tasks. Subjects were classified as inverse S-shaped if they chose the least risky [ambiguous] option at least twice in the small probability tasks and no more than once in the large probability tasks. Finally, they were classified as S-shaped if they chose the riskiest option at least twice in the small probability tasks and no more than once in the large probability tasks.

Figure 4.5 shows the classification of subjects for both risk and ambiguity. Inverse S is clearly the most common pattern. This is consistent with common findings (for risk, see e.g., Abdellaoui (2000) and Etchart-Vincent (2004), for ambiguity see e.g., Viscusi and Chesson (1999) and Baillon and Bleichrodt (2015)). Only a minority of the subjects behaved in line with the theoretically common assumptions of risk and ambiguity aversion. There are even substantially more subjects who were risk loving than risk averse.

Figure 4.5 Proportion of subjects by risk and ambiguity attitudes

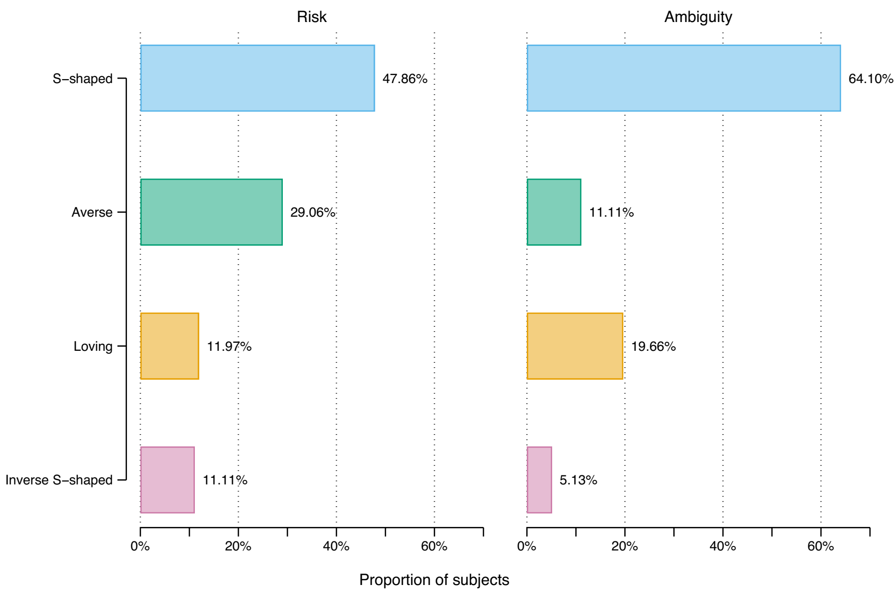


Figure 4.6 shows the subdivision of subjects depending on the number of risk prudent choices. The figure displays a tendency to risk prudence with on average 5.31 risk prudent choices across the 9 tasks. A Bayesian test gives decisive support for risk prudence over the null of risk imprudence or neutrality ($BF = 3.51 \times 10^6$). This is inconsistent with the findings of Bleichrodt and van Bruggen (forthcoming), who found risk imprudence for losses.

Finally, Figure 4.7 shows the subdivision of subjects depending on their number of ambiguity prudent choices. There is a slight tilt towards ambiguity imprudence. A Bayesian test shows support for the ambiguity imprudence over ambiguity prudence or neutrality ($BF = 24.13$). This finding goes against Baillon, Schlesinger and van de Kuilen (2018) who found predominant ambiguity prudence. However, they used gains whereas we use losses, which might explain the difference as this is consistent with a reflection effect for higher order preferences (Bleichrodt and van Bruggen, forthcoming).

Figure 4.6 Number of subjects choosing each number of risk prudent choices

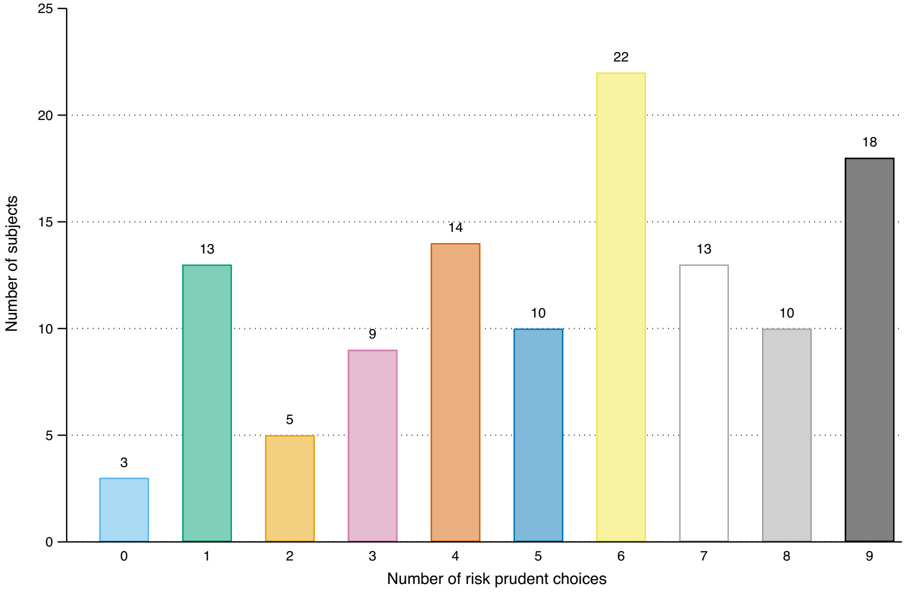
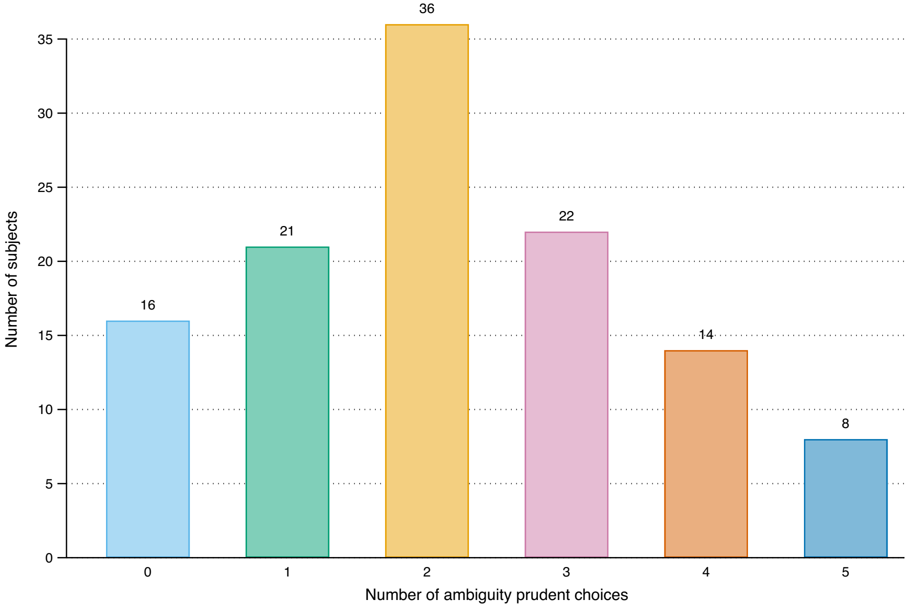


Figure 4.7 Number of subjects choosing each number of ambiguity prudent choices

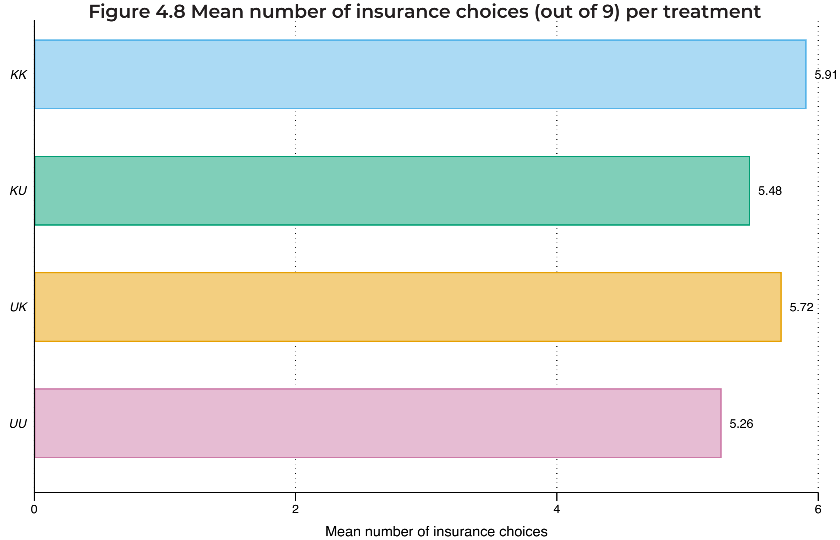


4.4.2.Insurance choices

The central question of our paper is how unknown insurable risks and nonperformance risks change insurance decisions compared to the case where these risks are known. Figure 4.8 shows the mean number of choices (out of 9) in which subjects chose the insurance option. The results illustrate that moving from a known to an unknown probability made the insurance option less attractive. This effect is particularly pronounced for the probability of nonperformance. Bayesian testing shows support for the hypothesis that subjects choose insurance more often when the nonperformance risk is known than when it is unknown (treatments *KK* and *UK* versus treatments *KU* and *UU*) (BF = 13.1).[72] However, when comparing choices for known and unknown insurable risks (treatments *KK* and *KU* versus treatments *UK* and *UU*), we find support for the null that the number of insurance choices is the same (BF = 0.18).

We obtain mixed results regarding the theoretical predictions outlined in Table 4.1. As mentioned in the previous paragraph, we find support for the prediction of Peter and Ying (2020) that an ambiguous nonperformance risk reduces the demand for insurance.[73] However, we find no support for Snow's (2011) prediction that insurance demand should be higher in treatment *UK* than in treatment *KK*. A Bayesian test supports the null that insurance demand was the same in these two treatments (BF = 0.13). Similarly, we find no support for the prediction derived by combining the results of Peter and Ying (2020) and Snow (2011) that the demand for insurance should be higher in treatment *UK* than in treatment *KU*. A Bayesian test again supports the null that the demand for insurance was the same in these two treatments (BF = 0.18).

Figure 4.8 Mean number of insurance choices (out of 9) per treatment



Notes: Treatments *KK*, *KU*, *UK* and *UU* indicate whether the insurable risk and nonperformance risk respectively are known (*K*) or unknown (*U*).

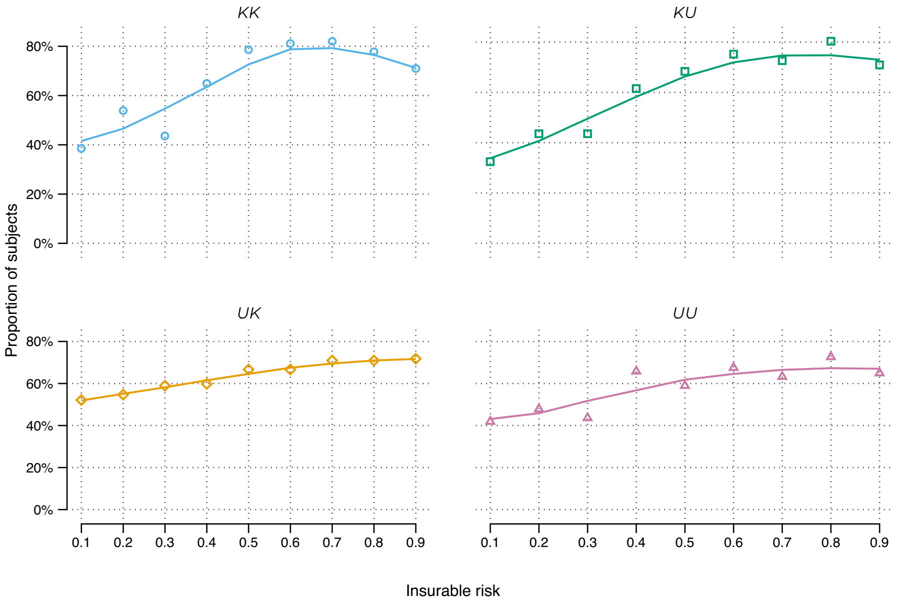
It should be kept in mind though that the theoretical predictions of Peter and Ying (2020) and Snow (2011) are made under the assumption that subjects are risk and ambiguity averse. We saw in Section 4.1 that this is true for most subjects for probabilities less than 0.5. The probability of nonperformance was always less than 0.5 in our experiment, but the insurable risk could exceed 0.5. An analysis of only those insurance choices in which the insurable risk was at most 0.4 confirmed all previous results with one important exception: Snow's (2011) prediction that subjects should be more inclined to choose insurance in treatment *UK* than in treatment *KK* was now very strongly supported (BF = 39.6).[74]

Figure 4.9 shows for each of the four treatments how the proportion of insurance choices varies with the insurable risk. There is a trend for subjects to choose insurance more often

72 We tested this using the contingencyBF function in the R package BayesFactor (Morey and Rouder 2018) with the assumption that the sampling type was joint multinomial.
73 However, if we separately compared treatments *KK* and *KU* and *UK* and *UU* the evidence was inconclusive (BF = 1.01 and BF = 1.46, respectively).
74 Most other tests were inconclusive.

when the insurable risk increases[75], particularly when it is known. Bayesian tests shows support for a positive correlation between the number of insurance choices and the insurable risk in all treatments (all $BF > 4.8$, taking all treatments together the $BF = 12.4$).

Figure 4.9 Proportion of insurance choices for each treatment by insurable risk



Notes: Treatments *KK*, *KU*, *UK* and *UU* indicate whether the insurable risk and nonperformance risk respectively are known (*K*) or unknown (*U*). Trend line fitted by loess method.

The dependence of insurance choice on the insurable risk is at odds with the predictions of inverse S-shaped weighting, the dominant pattern observed in our risk aversion tasks, if utility is linear and reduction of compound lotteries holds.[76] Inverse S with linear utility predicts that subjects will be more inclined to buy insurance for small than for large loss probabilities, which is the opposite pattern of what we observe. The same pattern emerges when we restrict the analysis to those subjects who were actually classified as inverse S in the analysis of risk attitudes described above. The pattern of insurance choices is consistent with S-shaped weighting, but the number of subjects displaying S- shaped weighting is too low to perform meaningful analyses. The assumption of reduction of compound lotteries is not innocuous (e.g., Bernasconi 1994). We therefore also analyzed the results under a recursive rank-dependent utility model, but this performed even worse (see Appendix 4.D for details).

To extend our understanding of what drives the observed insurance decisions, we performed probit analyses with the choices in our insurance tasks as the dependent variables. In line with theoretical predictions, the results in Table 4.2 show that an unknown nonperformance risk leads to less insurance demand. On the other hand, ambiguity of the insurable risk has no effect on insurance demand. The lower demand for insurance with unknown nonperformance risk cannot be attributed to our measure of ambiguity aversion. Because ambiguity preferences cannot impact insurance decisions in treatment *KK*, where all risks were known, and because ambiguity aversion is predicted to affect demand differently for different treatments, we included interaction terms of ambiguity preferences and our treatments.[77] None of the interaction terms is statistically significant.

75 This may sound trivial, but keep in mind that insurance was always actuarially fair, so the insurance premium also increased with the insurable risk. Jang and Hadar (1995) have shown that demand for actuarially fair insurance is not necessarily monotonic in the loss probability for a risk averse expected utility maximizer.
76 See Appendix 4.C for a derivation.
77 Note that although ambiguity preferences should not play a role for decisions without ambiguity, risk preferences may play a role in decisions with or without ambiguity. Hence, there is no need to similarly interact risk preferences with our treatments.

Ambiguity aversion has a positive impact only when it is included as a general variable for the subjects who had been classified as ambiguity averse (see Table 4.E1 in Appendix 4.E). However, this has no clear interpretation. Ambiguity prudence never affects the demand for insurance, but this should perhaps not come as a surprise given that its effect is not unequivocal as derived by Peter and Ying (2020).

Table 4.2 also shows that the insurable risk (p) has the largest marginal effect on insurance choice. It is positive, confirming that subjects were more inclined to choose the insurance option for higher loss probabilities. Subjects who were more risk averse chose insurance more often. The negative effects of risk prudence on insurance demand are in line with Eeckhoudt and Gollier (2005). Finally, we corrected for gender and nationality, the two main sources of variation in experimental studies.[78] Males were more likely to choose insurance, but nationality had no effect.[79 80]

Because the theoretical models discussed in Section 4.2 concentrate on the risk and ambiguity averse subjects, we also separately analyzed choices with insurable loss probabilities of at most 0.5, the range for which most subjects were risk and ambiguity averse. Table 4.3 shows that the results change somewhat. In this range, the effect of an unknown nonperformance risk becomes less pronounced. On the other hand, the uptake of insurance with an unknown insurable risk and known nonperformance risk is higher and becomes significant, as predicted by Snow (2011). Also, the effect of risk attitudes becomes more important. As the results reported in Appendix 4.E (Table 4.E2 and Figure 4.E1) suggest, consistent with the theoretical predictions of Jullien, Salanié and Salanié (1999), this is because risk aversion only increases insurance demand up to a threshold of p.

Table 4.2 Probit regression results

	Choose insurance	**Average marginal effect**	**Choose insurance**	**Average marginal effect**
KU	-0.13**	-0.05	-0.11	-0.04
	(0.05)	(0.02)	(0.09)	(0.03)
UK	-0.06	-0.02	-0.06	-0.02
	(0.05)	(0.02)	(0.08)	(0.03)
UU	-0.19***	-0.07	-0.17**	-0.06
	(0.06)	(0.02)	(0.09)	(0.03)
Risk aversion	0.07**	0.02	0.07**	0.02
	(0.03)	(0.01)	(0.03)	(0.01)
Risk prudence	-0.04**	-0.02	-0.04**	-0.02
	(0.02)	(0.01)	(0.02)	(0.01)
p	1.11***	0.40	1.11***	0.40
	(0.17)	(0.06)	(0.17)	(0.06)
AA×*KU*			0.01	0.01
			(0.13)	(0.05)
AA×*UK*			0.03	0.01
			(0.12)	(0.04)
AA×*UU*			-0.03	-0.01
			(0.12)	(0.04)
AP×*KU*			-0.08	-0.03
			(0.13)	(0.05)
AP×*UK*			-0.05	-0.02
			(0.12)	(0.04)

(continued on next page)

78 None of these was associated with insurance choices in the experiment.
79 Excluding gender and nationality does not affect the interpretation of our results.
80 Dummies for the holding of different types of real-life insurance were not correlated with the insurance choices in our experiment. This is perhaps not surprising, as the sample consisted of students, who typically have few assets to insure.

Table 4.2 (continued)

AP×*UU*			-0.02 (0.12)	-0.01 (0.04)
Male	0.23** (0.10)	0.08 (0.04)	0.23** (0.10)	0.08 (0.04)
Dutch	0.04 (0.10)	0.02 (0.04)	(0.04) (0.10)	0.02 (0.04)
Constant	-0.33 (0.21)		-0.34 (0.20)	

Notes: N = 4,176. Asterisks indicate a p-value < 0.05 (**) and < 0.01 (***). Robust standard errors between parentheses and clustered by subject. *KU*, *UK* and *UU* are treatment dummies indicating whether the insurable risk p and nonperformance risk q respectively are known (*K*) or unknown (*U*). Risk aversion and risk prudence are the number of risk averse and risk prudent choices (out of 9). AA is a dummy variable which takes the value of 1 if the subject chose the ambiguity averse option at least 5 times (out of 9). AP is a dummy variable which takes the value of 1 if the subject chose the ambiguity prudent option at least 3 times (out of 5). p is the insurable risk and can take any decimal value from 0.1 till 0.9.

Table 4.3 Probit regression results for insurable risks smaller than 0.5

	Choose insurance	Average marginal effect	Choose insurance	Average marginal effect
KU	-0.13* (0.08)	-0.05 (0.03)	-0.22* (0.12)	-0.08 (0.04)
UK	0.17** (0.09)	0.06 (0.03)	0.13 (0.12)	0.05 (0.04)
UU	-0.12 (0.08)	-0.04 (0.03)	-0.18 (0.12)	-0.06 (0.04)
Risk aversion	0.13*** (0.03)	0.05 (0.01)	0.14*** (0.03)	0.05 (0.01)
Risk prudence	-0.06** (0.03)	-0.02 (0.01)	-0.06** (0.03)	-0.02 (0.01)
p	1.71*** (0.27)	0.63 (0.10)	1.73*** (0.30)	0.63 (0.11)
AA×*KU*			0.29 (0.18)	0.10 (0.07)
AA×*UK*			0.13 (0.16)	0.05 (0.06)
AA×*UU*			0.25 (0.16)	0.09 (0.06)
AP×*KU*			-0.12 (0.19)	-0.04 (0.07)
AP×*UK*			-0.05 (0.17)	-0.02 (0.06)
AP×*UU*			0.12 (0.17)	0.05 (0.06)
Male	0.29** (0.13)	0.11 (0.05)	0.28** (0.13)	0.10 (0.05)
Dutch	0.05 (0.14)	0.02 (0.05)	0.05 (0.13)	0.02 (0.05)
Constant	-0.88*** (0.24)		-0.88*** (0.23)	

Notes: N = 1,856. Asterisks indicate a p-value < 0.05 (**) and < 0.01 (***). Robust standard errors between parentheses and clustered by subject. *KU*, *UK* and *UU* are treatment dummies indicating whether the insurable risk p and nonperformance risk q respectively are known (*K*) or unknown (*U*). Risk aversion and risk prudence are the number of risk averse and risk prudent choices (out of 9). AA is a dummy variable which takes the value of 1 if the subject chose the ambiguity averse option at least 5 times (out of 9). AP is a dummy variable which takes the value of 1 if the subject chose the ambiguity prudent option at least 3 times (out of 5). p is the insurable risk and can take any decimal value from 0.1 till 0.4.

4.5. Discussion

Our main conclusion is that an ambiguous nonperformance risk indeed leads to a reduction in insurance demand compared to a known nonperformance risk. Previous studies have already shown that nonperformance risk reduces the demand for insurance. We show that the more realistic case where the nonperformance risk is unknown further reduces the demand for insurance. This could help explain people's reluctance to take up insurance against for example natural disasters or long-term care needs. Our results may also help to understand why people fail to undertake prevention measures, which is equivalent to the full insurance decisions that we – like previous experiments on nonperformance risk – examine.

Previous theoretical studies have primarily analyzed insurance decisions with nonperformance risk by assuming that decision makers are risk and ambiguity averse. If we restrict attention to the choices for which most subjects were risk or ambiguity averse, then most of these predictions were supported. Risk aversion leads to more insurance demand, while risk prudence reduces it, which is consistent with theoretical predictions (Dionne & Eeckhoudt 1985; Eeckhoudt & Gollier 2005). We can also confirm Peter and Ying's (2020) prediction that an ambiguous nonperformance risk leads to less insurance than a known nonperformance risk. At probabilities for which most individuals are risk and ambiguity averse, we found support for Snow's (2011) prediction that ambiguity of the insurable risk leads to more insurance demand.

Although we find that ambiguity of the nonperformance risk decreases the demand for insurance, ambiguity aversion did not appear to drive this effect in our regression analysis. In the analysis, ambiguity aversion was included as a dummy indicating whether a subject mostly chose the ambiguity averse option or not, consistent with the theoretical literature where ambiguity aversion is taken as a universal preference.[81] Our data shows that the assumption of uniform risk and ambiguity aversion is too restrictive. Most subjects displayed the common empirical pattern of risk and ambiguity aversion for small loss probabilities and risk and ambiguity seeking for larger loss probabilities. A general ambiguity aversion variable cannot capture this diversity of ambiguity preferences within subjects and may therefore fail to fully pick up the effects of ambiguity averse (or seeking) preferences.

We find that most subjects are risk prudent, which goes against Bleichrodt and van Bruggen (forthcoming) who find clear evidence of risk imprudence for losses. The different findings may be due to differences in presentation: to ensure internal consistency with the presentation of the insurance tasks, the presentation of the prudence tasks in our experiment differed from the presentation in Bleichrodt and van Bruggen (forthcoming).[82] We find evidence of ambiguity imprudence for losses, which is consistent with the reflection effect for higher order risk preferences observed by Bleichrodt and van Bruggen (forthcoming) and the predominant ambiguity prudence observed by Baillon, Schlesinger and van de Kuilen (2018) for gains.

The dependence of insurance choices on the insurable risk remains puzzling. Experimental research has long found (and been unable to explain) a similar dependency in actuarily fair insurance choices without nonperformance risk (Slovic, Fischhoff, Lichtenstein, Corrigan & Combs 1977). As we pointed out, this dependency is inconsistent with inverse S-shaped probability weighting if utility is linear. Usually empirical studies find that utility is close to linear for the stakes involved in our study. This poses the question about the external validity of elicited risk preferences: to what extent can they explain other choices people make? We are not alone in observing that inverse S-shaped probability weighting does not predict choice behavior well. Baillon, Capuno, O'Donnell, Tan, and van Wilgenburg (2019) performed a field experiment in the Philippines in which they tried

81 Peter and Toquebeuf (2020) propose a framework that allows to formally derive results for ambiguity lovers, who often exhibit reversed behavior.

82 The difference was not due to the inclusion of the insurance task, as we found no difference in risk prudent choices between the subjects who started with the elicitation of risk and ambiguity attitudes and those who started with the insurance choices.

to nudge health behavior but did not observe the pattern predicted by inverse S-shaped weighting. Jaspersen, Ragin, and Sydnor (forthcoming) explored to what extent models of decision under risk can predict insurance choices. While they found that these insurance choices were coherent and correlated with measures of risk attitude, the models they explored (which included expected utility and prospect theory) predicted these choices poorly and generally performed worse than simple heuristics.

Our results offer insights into the demand for long-term care insurance, which can benefit both policy makers and insurers. Uncertainty about the pay-out of future claims reduces insurance demand. Reducing such ambiguity could increase insurance uptake. This can be achieved through, for example, a common guarantee fund that insures against insurer bankruptcy. When such funds are already in place, increased awareness and transparency may further reduce ambiguity. The premium increase people would be willing to pay for such ambiguity reducing guarantees can be examined in future research. If needed, governments could support or subsidize such guarantees. Our study suggests that it is a worthwhile avenue to explore.

4.6. Conclusion

An important policy puzzle is why people underinsure against uncertain losses that occur in the far future, such as long-term care needs. Our results show that one possible reason is the unknown nonperformance risk that comes with such insurance. Our results are largely consistent with the predictions made by theoretical models. An ambiguous nonperformance risk decreased the demand for insurance compared with a known nonperformance risk. Risk attitudes play an important role in explaining insurance demand: risk aversion increases insurance demand, while risk prudence reduces it. The effect of ambiguity attitudes was less clear, probably because they are richer than ambiguity aversion alone.

4.7. Appendices

A. Experiment tasks

Table 4.A1 Insurance tasks for losses

No insurance				Insurance					
$1-p$	0	p	$-L$	$1-p$	$-\pi$	$p(1-q)$	$-\pi$	pq	$-\pi-L$
0.9	€0.00	0.1	-€17.50	0.9	-€1.40	0.1*0.8	-€1.40	0.1*0.2	-€18.90
0.8	€0.00	0.2	-€17.50	0.8	-€3.15	0.2*0.9	-€3.15	0.2*0.1	-€20.65
0.7	€0.00	0.3	-€15.00	0.7	-€2.70	0.3*0.6	-€2.70	0.3*0.4	-€17.70
0.6	€0.00	0.4	-€15.00	0.6	-€3.60	0.4*0.6	-€3.60	0.4*0.4	-€18.60
0.5	€0.00	0.5	-€16.00	0.5	-€5.60	0.5*0.7	-€5.60	0.5*0.3	-€21.60
0.4	€0.00	0.6	-€12.50	0.4	-€6.75	0.6*0.9	-€6.75	0.6*0.1	-€19.25
0.3	€0.00	0.7	-€10.00	0.3	-€5.60	0.7*0.8	-€5.60	0.7*0.2	-€15.60
0.2	€0.00	0.8	-€14.00	0.2	-€5.60	0.8*0.5	-€5.60	0.8*0.5	-€19.60
0.1	€0.00	0.9	-€14.00	0.1	-€6.30	0.9*0.5	-€6.30	0.1*0.5	-€20.30
0.8	€0.00	0.2	-€17.50	0.8	-€3.15	0.2*0.9	-€3.15	0.2*0.1	-€20.65

Table 4.A2 Insurance tasks for gains

No insurance				Insurance					
$1-p$	0	p	G	$1-p$	π	$p(1-q)$	π	pq	πG
0.9	€0.00	0.1	€55.00	0.9	€4.40	0.1*0.8	€4.40	0.1*0.2	€59.40
0.7	€0.00	0.3	€65.00	0.7	€11.70	0.3*0.6	€11.70	0.3*0.4	€76.70
0.5	€0.00	0.5	€58.00	0.5	€20.30	0.5*0.7	€20.30	0.5*0.3	€78.30
0.3	€0.00	0.7	€70.00	0.3	€39.20	0.7*0.8	€39.20	0.7*0.2	€109.20
0.1	€0.00	0.9	€40.00	0.1	€18.00	0.9*0.5	€18.00	0.1*0.5	€58.00

Table 4.A3 Risk aversion tasks

Risk averse				Risk seeking			
$1-p$	$-r$	p	$-k$	$1-p$	0	p	$-k-\frac{1-p}{p}r$
0.9	-€1.00	0.1	-€6.00	0.9	€0.00	0.1	-€15.00
0.8	-€3.50	0.2	-€6.00	0.8	€0.00	0.2	-€20.00
0.7	-€3.00	0.3	-€9.00	0.7	€0.00	0.3	-€16.00
0.6	-€8.00	0.4	-€6.00	0.6	€0.00	0.4	-€18.00
0.5	-€10.00	0.5	-€11.00	0.5	€0.00	0.5	-€21.00
0.4	-€6.00	0.6	-€10.00	0.4	€0.00	0.6	-€14.00
0.3	-€3.50	0.7	-€11.00	0.3	€0.00	0.7	-€12.50
0.2	-€10.00	0.8	-€15.00	0.2	€0.00	0.8	-€17.50
0.1	-€9.00	0.9	-€18.00	0.1	€0.00	0.9	-€19.00

Table 4.A4 Risk prudence task

Risk prudent			Risk imprudent		
$-x-k$	$-x+s$	$-x-s$	$-x$	$-x-k+s$	$-x-k-s$
-€11.00	-€2.00	-€10.00	-€6.00	-€7.00	-€15.00
-€13.00	-€2.00	-€12.00	-€7.00	-€8.00	-€18.00
-€14.00	-€4.00	-€16.00	-€10.00	-€8.00	-€20.00
-€13.00	-€3.00	-€7.00	-€5.00	-€11.00	-€15.00
-€16.00	-€3.00	-€9.00	-€6.00	-€13.00	-€19.00
-€13.00	-€2.00	-€18.00	-€10.00	-€5.00	-€21.00
-€15.00	-€6.00	-€16.00	-€11.00	-€10.00	-€20.00
-€14.00	-€3.00	-€15.00	-€9.00	-€8.00	-€20.00
-€14.00	-€2.00	-€10.00	-€6.00	-€10.00	-€18.00

Notes: Sure amount c has been deducted such that all outcomes are negative. $-x-k$ and $-x+\tilde{\varepsilon}$ both occur with probability 0.5 (with $-x+s$ and $-x-s$ occurring with probability 0.25).

Table 4.A5 Ambiguity aversion tasks

Ambiguity averse				Ambiguity seeking			
$1-p$	0	p	$-k$	$1-p+\tilde{\varepsilon}$	0	$p+\tilde{\varepsilon}$	$-k$
0.9	€0.00	0.1	-€17.50	0.9	€0.00	0.1	-€17.50
0.8	€0.00	0.2	-€15.00	0.8	€0.00	0.2	-€15.00
0.7	€0.00	0.3	-€16.00	0.7	€0.00	0.3	-€16.00
0.6	€0.00	0.4	-€10.00	0.6	€0.00	0.4	-€10.00
0.5	€0.00	0.5	-€18.00	0.5	€0.00	0.5	-€18.00
0.4	€0.00	0.6	-€21.00	0.4	€0.00	0.6	-€21.00
0.3	€0.00	0.7	-€12.50	0.3	€0.00	0.7	-€12.50
0.2	€0.00	0.8	-€19.00	0.2	€0.00	0.8	-€19.00
0.1	€0.00	0.9	-€20.00	0.1	€0.00	0.9	-€20.00

Table 4.A6 Ambiguity prudence tasks

Ambiguity prudent				Ambiguity imprudent			
$p+k$	$q-\varepsilon$	$q+\varepsilon$	$-L$	p	$q-\varepsilon+k$	$q+\varepsilon+k$	$-L$
0.9	0.1	0.6	-€17.00	0.5	0.5	1.0	-€17.00
0.8	0.2	0.7	-€15.00	0.5	0.5	1.0	-€15.00
0.7	0.3	0.8	-€14.00	0.5	0.5	1.0	-€14.00
0.8	0.2	0.8	-€13.00	0.6	0.4	1.0	-€13.00
0.7	0.3	0.7	-€11.00	0.4	0.6	1.0	-€11.00

Note: $q-\varepsilon$ and $q+\varepsilon$ are the lower and upper bound of the uncertainty interval $q+\tilde{\varepsilon}$

Figure 4.A1 Example of a risk aversion task

If your envelope contains this choice, which option would you like us to play out for real?

Figure 4.A2 Example of a risk prudence task

If your envelope contains this choice, which option would you like us to play out for real?

Figure 4.A3 Example of an ambiguity aversion task

If your envelope contains this choice, which option would you like us to play out for real?

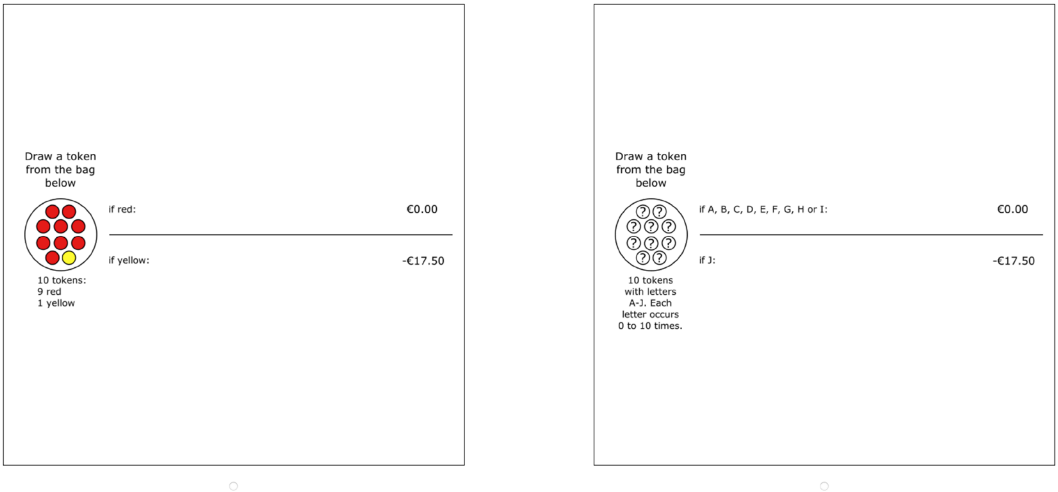
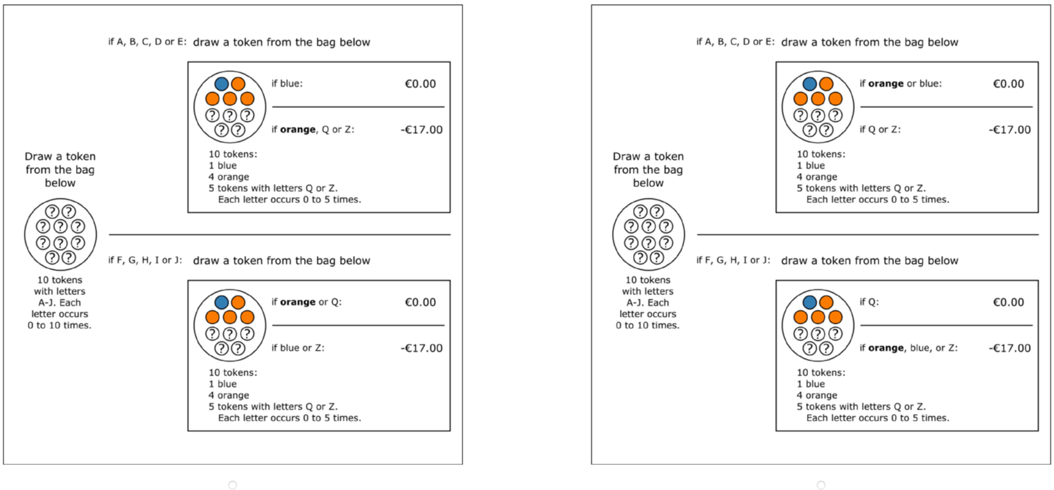


Figure 4.A4 Example of an ambiguity prudence task

If your envelope contains this choice, which option would you like us to play out for real?



B. Instructions

B1. Instructions before entering the cubicles

Welcome all and thank you for participating.

You will be asked to make 92 choices between two options involving monetary outcomes.

Before starting the experiment, you receive €25. If you choose not to finish the experiment you will have to return this money. Before starting, you will also select one of 92 closed envelopes. You are not allowed to open the envelope. Each sealed envelope represents one of the decision tasks. The decision task that envelope you have selected contains, will be played out for real after you have finished all choice tasks. The outcomes of the decision tasks range from -€21.00 to +€109.20.

The experiment will start with an explanation of the decision tasks. If you have any questions, one of us will be available in the control room between the cubicles. If you have finished the experiment, you can report back to the control room and you will be asked to wait in your cubicle until everyone has finished.

You can now – one by one – collect your €25, select an envelope. We will also number your envelope. You can enter this number in the first question. When everyone has received money and an envelope, we will walk to the cubicles.

B2. Instructions in the cubicles before the experiment

General

- You will be asked to make 92 choices between two options involving monetary outcomes under risk and uncertainty.
- These questions are divided over 12 parts, all of which start with 1 practice question.
- Additionally, you will be asked to answer 4 background questions.
- After the instructions, you will be asked to answer 5 practice questions.
- Except for the practice questions, there are no 'right' or 'wrong' answers. We are only interested in your preferences.
- You can withdraw at any time. By withdrawing you forego the entitlement to any compensation; you will then have to return the €25.00 show-up fee.

Compensation

- Compensation consists of a show-up fee and a variable pay.
- You have received a show-up fee of €25.00, conditional on completing all 92 choices and 4 background questions.
- The variable pay will be determined as follows:
- You have drawn a sealed envelope containing one of these 92 choices (a number from 1 to 92).
- Thus each choice has an equal chance to be selected.
- Your envelope will be opened when everybody has finished all choices and background questions. Thus, if you finish early, you might have to wait for the others to finish.
- The option that you have chosen in that particular choice will then be played out and paid for real.
- The possible outcomes of the variable pay range from -€21.60 to +€109.20 (with an average of €0.00) in addition to the show-up fee of €25.00.

Rules

- Talking, eating or drinking anything other than water is not allowed.
- Please turn off your cell phone now.
- Whenever you have a question, please raise your hand. A member of staff will answer your question in private.

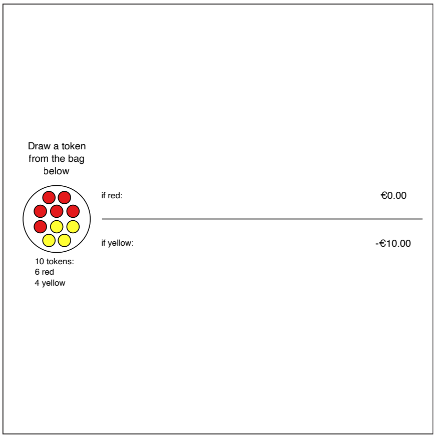
Choice tasks

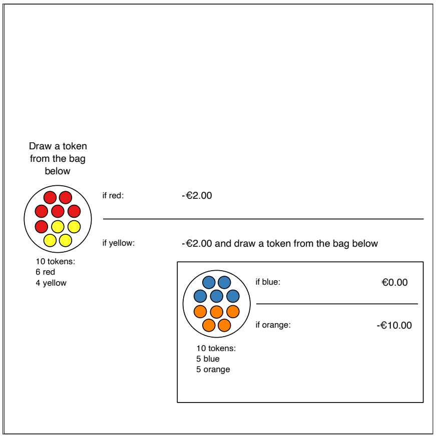
- You will be asked to make choices between two options.
- All options require drawing a token from one or two bags.
- All bags contain 10 tokens of one or more colors or letters.
- A legend is shown next to each bag, stating for each possible token in that bag what the consequence are when that token is drawn. This can be:
  - losing money;
  - gaining money;
  - neither losing nor gaining money; and
  - drawing a token from another bag.
- You can change your response to a previous question within the same part by returning to that question using the 'back' button.

Example

If you draw a yellow token, when playing out the option below:

- if you have chosen the option on the left-hand side, you lose €10.00.
- if you have chosen the option on the right-hand side, you lose €2.00 and you have to draw a token from another bag with blue and orange tokens. Then:
  - if you draw a blue token, you lose nothing in addition to your loss of €2.00. Hence, you lose €2.00 in total.
  - if you draw an orange token, you lose €10.00 in addition to your loss of €2.00. Hence, you lose €12.00 in total.





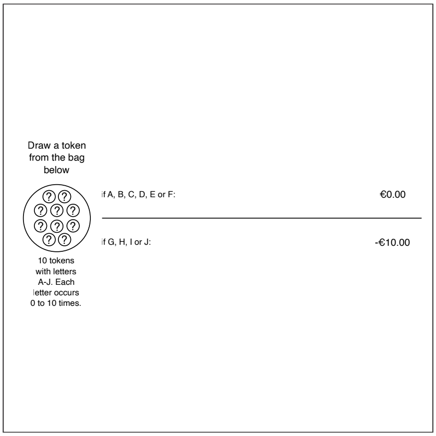
Uncertainty

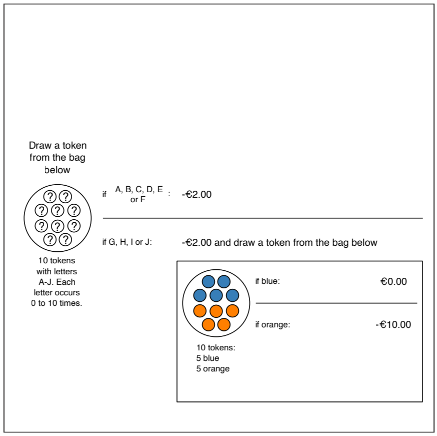
- Some bags are depicted with 10 question-marked tokens. We call these "bags of unknown composition".
- "Bags of unknown composition" contain 10 tokens with letters. Each letter occurs 0 to 10 times.
- These bags have been randomly filled with 10 tokens before the start of this session, based on the instructions of someone not affiliated with this research and who does not know the purpose of these bags.
- These letters can be any combination of the letters A-J or the letters Q-Z.
- Whether "bags of unknown composition" contain combinations of the letters A-J or of the letters Q-Z is shown in the legend underneath the bags.
- After the practice questions, you will be asked to rank the letters (A-J or J-A and Q-Z or Z-Q).
- This ranking will be used to play out for real the choice task that your envelope contains.

Example

If you draw a token with the letter H, when playing out the option below:

- if you have chosen the option on the left-hand side, you lose €10.00.
- if you have chosen the option on the right-hand side, you lose €2.00 and draw a token from another bag with blue and orange tokens. Then:
  - if you draw a blue token, you lose nothing in addition to your loss of €2.00. Hence, you lose €2.00 in total.
  - if you draw an orange token, you lose €10.00 in addition to your loss of €2.00. Hence, you lose €12.00 in total.





C. Probability weighting

Under linear utility, which is commonly observed for choices involving only small stakes, no single probability weighting function can explain the majority choices that we observe in our risk aversion and insurance tasks under rank-dependent utility. To illustrate this, let's first look at our risk aversion tasks. Under rank-dependent utility we can write the observed majority choice for $p = 0.1$ as:

$$w(0.1) \cdot (-15) + (1 - w(0.1)) \cdot 0 < w(0.1) \cdot (-6) + (1 - w(0.1)) \cdot (-1).$$

The inequality sign here implies that most of our respondents chose the risk averse option. We can simplify this to $w(0.1) > 0.1$, which implies that most respondents overweighed this probability. Similarly, we find the following implied probability weights for our other risk aversion tasks:

$$\begin{gathered} w(0.2) > 0.2 \\ w(0.3) > 0.3 \\ w(0.4) > 0.4 \\ w(0.5) > 0.5 \\ w(0.6) \sim 0.6 \\ w(0.7) < 0.7 \\ w(0.8) < 0.8 \\ w(0.9) < 0.9 \end{gathered}$$

Hence, we find probability overweighting for $0.1 \leq p \leq 0.5$ and underweighting for $0.7 \leq p \leq 0.9$. This pattern is consistent with inverse S-shaped probability weighing, which predicts overweighting of small probabilities and underweighting of large probabilities.

Let's next consider the insurance tasks. Under rank-dependent utility with loss ranks we can write the observed majority choice for $p = 0.1$ as:

$$w(0.1) \cdot (-17.5) + (1 - w(0.1)) \cdot 0 > w(0.02) \cdot (-18.9) + (1 - w(0.02)) \cdot (-1.4).$$

We can simplify this to $w(0.1) < \mathrm{w}(0.02) + 0.08$. Similarly, we find the following implied probability weights for our other insurance tasks:

$$\begin{gathered} w(0.2) \sim w(0.02) + 0.18 \\ w(0.3) < w(0.12) + 0.18 \\ w(0.4) > w(0.16) + 0.24 \\ w(0.5) > w(0.15) + 0.35 \\ w(0.6) > w(0.06) + 0.54 \\ w(0.7) > w(0.14) + 0.56 \\ w(0.8) > w(0.40) + 0.40 \\ w(0.9) > w(0.45) + 0.45 \end{gathered}$$

Note that the numbers on the right of the inequality signs sum to the number on the left. The final three inequalities show that the weights of probabilities 0.7, 0.8 and 0.9 (on the left-hand side) must be overweighed, as they must be greater than (on the right-hand side) the sum of a linear probability weight and the weights of probabilities smaller than 0.5, and the latter were found to be overweighed in the risk aversion tasks. Yet the probabilities bigger than 0.7 were found to be underweighted in the risk aversion tasks, a contradiction.

Hence, rank dependent utility with linear utility cannot explain our majority choices.

D. Recursive rank dependent utility

The reason why probability weighting (in the form of rank dependent utility) cannot capture our findings is that for the risk aversion tasks, we find risk aversion for probabilities (of the worst outcome) between 0.1 and 0.5 and risk loving choices for probabilities between 0.6 and 0.9, which indicates inverse S-shaped probability weighting. Such inverse S probability weighting implies that insurance should be attractive when the insurable risk is small. Yet, subjects, on average, chose not to buy insurance for the probabilities, and did for larger insurable risks. One possible explanation for this apparent contradiction is that subjects do weigh probabilities but violate the reduction of compound lotteries axiom. After all, risk aversion was measured with a single-stage task, whereas the insurance option involves two stages. However, as we show in this Appendix, allowing for such violations does not help to accommodate our findings.

Recursive rank dependent utility (as applied by e.g., Freeman (2017)) is a form of probability weighting that allows for violations of the reduction of compound lotteries axiom when applying probability weighting. It works by first evaluating the second stage according to rank dependent utility with some probability weighting function $w(p)$, calculating the certainty equivalent of the second stage, and then substituting this certainty equivalent of the second stage in the first stage. The first stage is then evaluated according to rank dependent utility, using the same probability weighting function $w(p)$ as in evaluating the second stage, which means the procedure satisfies Segal's (1990) time neutrality axiom.

A first observation is that, for a given probability weighting function, the evaluation of the risk aversion tasks and the no insurance option are the same for rank dependent utility and its recursive form, because they involve only one stage. Therefore, the choices for the risk aversion tasks still indicate inverse S probability weighting. As it turns out, the insurance option is even more attractive for small insurable risks under recursive rank dependent utility than under rank dependent utility with inverse S probability weighting.

To see this, we can write out the utility representation of the insurance option under rank dependent utility:

$$w(pq)(-\pi - L) + [1 - w(pq)](-\pi).$$

Under recursive rank dependent utility, the value of the second stage is

$$w(q)(-\pi - L) + [1 - w(q)](-\pi)$$

and substituting this into the representation of the first stage, the value of the insurance option is

$$w(p)[w(q)(-\pi - L) + [1 - w(q)](-\pi)] + [1 - w(p)](-\pi).$$

Thus, under rank dependent utility the weight on the best outcome, $-\pi$, is

$$[1 - w(q)]$$

whereas under recursive rank dependent utility it is

$$[1 - w(p)w(q)]$$

which is obviously bigger. Thus, under recursive rank dependent utility, the best outcome of the insurance option is weighted more strongly than under rank dependent utility, which makes insurance more attractive. Given that the difficulty was with accommodating the distaste for some of the insurance options, recursive rank dependent utility cannot accommodate this.

E. Supplementary analyses

Table 4.E1 Probit regression with the number of ambiguity averse and prudent choices

	Choose insurance	Average marginal effect
KU	-0.13**	-0.05
	(0.05)	(0.02)
UK	-0.06	-0.02
	(0.06)	(0.02)
UU	-0.20***	-0.07
	(0.06)	(0.02)
Risk aversion	0.07***	0.03
	(0.03)	(0.01)
Risk prudence	-0.05**	-0.02
	(0.02)	(0.01)
p	1.11***	0.39
	(0.18)	(0.06)
Ambiguity aversion	0.04*	0.02
	(0.03)	(0.01)
Ambiguity prudence	0.00	0.00
	(0.03)	(0.01)
Male	0.22**	0.08
	(0.10)	(0.04)
Dutch	0.05	0.02
	(0.10)	(0.04)
Constant	-0.55**	
	(0.25)	

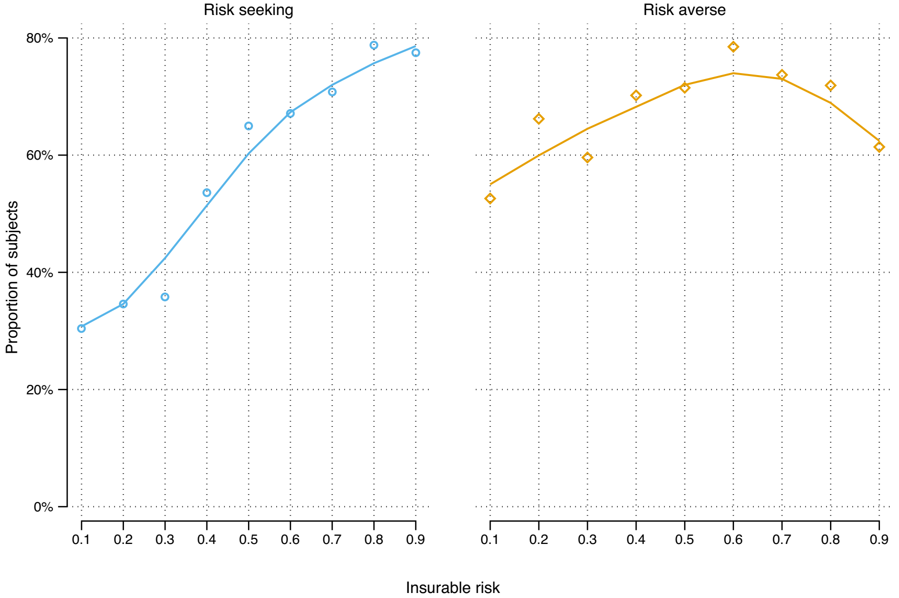
Notes: N = 4,176. Asterisks indicate a p-value < 0.05 (**) and < 0.01 (***). Robust standard errors between parentheses and clustered by subject. *KU*, *UK* and *UU* are treatment dummies indicating whether the insurable risk and nonperformance risk respectively are known (*K*) or unknown (*U*). Risk aversion, risk prudence and ambiguity aversion are the number of risk averse, risk prudent and ambiguity averse choices (out of 9). Ambiguity prudence is the number of ambiguity prudent choices (out of 5). p is the insurable risk and can take any decimal value from 0.1 till 0.9.

Table 4.E2 Probit regression interacting risk aversion with a large insurable risk

	Choose insurance	Average marginal effect
KU	-0.14**	-0.05
	(0.05)	(0.02)
UK	-0.06	-0.02
	(0.06)	(0.02)
UU	-0.20***	-0.07
	(0.06)	(0.02)
Risk aversion	0.13***	0.04
	(0.03)	(0.01)
Risk prudence	-0.04**	-0.02
	(0.02)	(0.01)
p	1.08***	0.38
	(0.20)	(0.06)
Risk aversion	-0.11***	-0.04
	(0.04)	(0.01)
Male	0.23**	0.08
	(0.10)	(0.04)
Dutch	0.05	0.02
	(0.10)	(0.04)
Constant	-0.37	
	(0.20)	

Notes: N = 4,176. Asterisks indicate a p-value < 0.05 (**) and < 0.01 (***). Robust standard errors between parentheses and clustered by subject. *KU*, *UK* and *UU* are treatment dummies indicating whether the insurable risk and nonperformance risk respectively are known (*K*) or unknown (*U*). Risk aversion, risk prudence and ambiguity aversion are the number of risk averse, risk prudent and ambiguity averse choices (out of 9). Ambiguity prudence is the number of ambiguity prudent choices (out of 5). p is the insurable risk and can take any decimal value from 0.1 till 0.9.

Figure 4.E1 Proportion of insurance choices for more risk seeking and risk averse individuals by insurable risk.



Notes: Risk seeking means less than 5 risk averse choices. Risk averse means more than 4 risk averse choices. Trend line fitted by loess method.

6

Insurance coverage and demand for mental health care

Empirical evidence suggests that people are fairly sensitive to cost sharing arrangements in ambulatory mental health care. However, pure cost sharing effects are typically hard to measure due to the presence of adverse selection effects. In this paper we examine the impact of cost sharing on mental health care utilization in the context of mandatory health insurance where adverse selection is absent. Using a large proprietary dataset of a Dutch private health insurer, we examine to what extent a new copayment scheme for adult mental health care changed health care utilization. We exploit the fact that non-adults are exempted from copayments. First, we compare changes in utilization among adults and non-adults using *t*-tests and a difference-in-difference analysis. Second, we highlight differential changes in mental health care utilization by treatment (duration and type of mental illness) and individual characteristics (gender and socioeconomic status). Third, we evaluate to what extent anticipatory behavior occurred pending the introduction and subsequent repeal of the new copayment scheme. Our results show a strong and significant ($p < 0.01$) decrease in outpatient secondary mental health care utilization among adults following the introduction of copayments, that is absent among non-adults. This decrease is concentrated among treatments for less severe mental illnesses. Furthermore, the utilization patterns suggest the presence of anticipatory behavior.

Based on:
"The impact of copayments on mental healthcare utilization:
a natural experiment"

with René van Vliet
in The European Journal of Health Economics, 19(6), 775-784.

6. Insurance coverage and demand for mental health care

6.1. Introduction

Effects of cost sharing seem particularly strong for mental health care. Specifically, Frank and McGuire (2000) show that: "nearly all the available evidence, experimental or observational, points in the direction of greater price response for ambulatory [outpatient] mental health than other health care services" (p. 911). Yet, with the exception of the RAND Health Insurance Experiment (HIE) (Keeler et al. 1988) such observational research is subject to adverse selection (Ellis & McGuire 1986). Adverse selection likely leads to an underestimation of price responses for the population at large; when individuals can freely decide whether or not to purchase health insurance, the pool of insureds will consist mainly of individuals with relatively bad health states, who will respond less to price changes. Furthermore, evidence of price responses for mental health care outside the US is still mostly indirect and mainly comprises research on under and overtreatment of mental disorders, rather than on price responses per se (Frank 2011). In contrast, this paper aims to investigate the pure copayment effects (i.e., without adverse selection effects) for outpatient mental health care in a non-US context where adverse selection does not play a role due to both mandatory health insurance and mandatory copayments. This is especially relevant as the benefits of copayments within Europe are increasingly being questioned by both scholars (e.g., Drummond & Towse 2012) and policy makers (Expert Panel on effective ways of investing in Health 2016).

In addition, this paper contributes to existing knowledge in two other ways. First, by estimating the differential impact of price on mental health care utilization by type of treatment, by gender and by socioeconomic status, we contribute to the limited knowledge in this area. This is relevant because other studies indicate that particularly males and people with lower socioeconomic status are vulnerable to underutilization of mental health services (Bijl et al. 2003). Second, we examine whether people anticipate changes in copayments. Evidence on anticipatory behavior is limited, because most research is either survey-based (Horgan 1986; McGuire 1981; Taube, Kessler & Burns 1986) or prone to adverse selection effects selection (Ellis & McGuire 1986). Moreover, a recent empirical study shows that anticipatory behavior is important for an appropriate evaluation of the effect of cost sharing (Brot-Goldberg et al. 2017).

This research utilizes changes of copayments in the Dutch universal mandatory health insurance scheme to analyze price responsiveness for mental health care. In 2012, existing copayments for primary mental health care were raised and new copayments were introduced for secondary mental health care in the Netherlands. Using a large proprietary dataset of a private Dutch health insurer, we are able to examine the pure effect of these changes for outpatient mental health care. We do so by comparing changes in health care utilization between those who are affected by these changes in copayments (adults) and those who are not affected (non-adults).

In sum, the goal of this paper is threefold and consists of: (1) estimating the pure demand response for outpatient mental health services, net of selection effects and in another setting than the US; (2) estimating differences in demand varying with treatment, gender and socioeconomic status; and (3) evaluating the occurrence of anticipatory behavior in response to changes in cost sharing regime.

6.2. Previous research

Economic theory predicts that people use fewer mental health care services when cost sharing is introduced or increased in their insurance coverage. The magnitude of decreases in health care utilization depends on the extent of cost sharing and the elasticity of demand. The RAND HIE found a price elasticity of general health care between -0.10

and -0.14 for coinsurance rates between 0-25 and 25-95 percent respectively (Manning et al. 1987). Other research reported similar results in various countries and at various points in time (Frank & McGuire 2000; Kill & Houlberg 2014). Research focusing specifically on outpatient mental health care suggests that the price elasticity of such care is larger than that of general medical care, as scholars found price elasticities of -0.79 and -0.31 respectively for coinsurance rates between 25 and 95 percent (Keeler et al. 1988). Research in the Netherlands delivered similar results with price elasticities of -0.14 for cost sharing arrangements in general health care (van Vliet 2004). These elasticities differed greatly between health care services, with a price elasticity of -0.40 for visits to the general practitioner and -0.08 for prescription drug and were found to increase with the extent of cost sharing. Otherwise, most evidence of price effects in mental health care outside the US is still indirect. Notably, such evidence suggests that receiving a treatment is strongly associated with disorder severity as well as positively correlated with age, level of education and the female gender (Bijl et al. 2003).

There are three possible explanations for differences in price elasticities between mental health care and other health care services. First, it is argued that elasticities differ because of the necessity of treatments (van Vliet 2004; Sinnott et al. 2015); it is presumably easier to forego a visit to a general practitioner for a minor ache than to forego a visit to the hospital for a broken leg. In the same way, mental illnesses could be perceived as less acute than that same broken leg and could hence be easier foregone. Second, the willingness to seek professional help in mental health care is likely restrained by fears of stigmatization (Bijl et al. 2003). Third, an increasing number of people have pessimistic perceptions of the effectiveness of mental health care and sometimes even prefer to wait until a mental illness fades by itself (Prins et al. 2011). Copayments could interact with and aggravate these tendencies to undertreat mental disorders and thus lead to differences in copayment effects vis-a-vis other health care services.

Furthermore, anticipation effects (or ex ante moral hazard) play a role in shaping responses to cost sharing. Price responses do not merely embody a binary choice between using and not using health care at a given cost sharing level. Rather, by adequately timing health care consumption such that health care is used when copayments are lowest, patients can minimize cost sharing. Changes in insurance coverage that are announced beforehand thus create opportunities for ex ante moral hazard if health care consumption can be scheduled. A recent study among employees whose firm discontinued a health plan with generous first-dollar coverage to only retain a high-deductible health plan for example found that this shift reduced health care utilization by 19 percent (Brot-Goldberg et al. 2017). Yet, when correcting for anticipatory behavior, only an 11-15 percent decrease in health care utilization could be attributed to the high-deductible health plan. Hence, ex ante moral hazard may increase measured price elasticities in natural experiments by spurring demand prior to the introduction of new cost sharing arrangements to substitute for expected demand after that introduction.

6.3. Empirical setting

The Dutch health care system is characterized by a universal mandatory basic health insurance scheme, covering all essential health care services with a standardized benefits package for the entire population. Basic health insurance coverage is offered by private health insurers in return for a community-rated premium. The basic benefits package, a mandatory deductible for most health care services and copayments are all set by the national government.

The provision of Dutch mental health care can be distinguished in primary and secondary care. In our study period 28 percent of the mental health patients received primary care and 77 percent secondary care (NZa 2015). Primary care, which is accessible without referral, offers treatments for relatively mild disorders. Secondary care consists of treatments of more serious conditions that need specialized care. In secondary mental health care, a further distinction can be made between curative care and long-term – often institutionalized – care. To gain access to secondary mental health care a referral from a general practitioner or primary mental health care provider is required.

Since 2008, most mental health care services have been included in the basic health insurance, with the exception of chronic mental disorders and long-term mental health care[106], which are insured through a social long-term care insurance. Coverage for primary mental health care had been limited to eight sessions per year, all subject to a copayment of €10 per session. The cost sharing reforms, summarized in Table 6.1, encompassed both an increase of existing primary mental health care copayments and the introduction of a new copayment for secondary care. In primary care, existing copayments were increased from €10 to €20 per session and the number of sessions covered in the basic health insurance was reduced from eight to five. In secondary care, a copayment of €100 per 100 minutes, capped at €200 annually was introduced.[107] These secondary care copayments were repealed again at the start of 2013. Furthermore, the reforms comprised the removal of adjustment disorders from the basic health insurance benefit package. At the same time, the mandatory deductible increased with €180 between 2011 and 2013. Finally, non-adults, constituting 23 percent of all Dutch mental health patients between 2011 and 2013 (NZa 2015), were exempted from paying any copayments or deductibles between 2011 and 2013. This exemption hence creates a convenient control group to analyze the effects of introducing and increasing copayments.

Table 6.1 Cost sharing for adult mental health care between 2011 and 2013

Cost sharing	2011	2012	2013
Primary mental healthcare copayments	€10 (a)	€20 (b)	€20 (b)
Secondary mental healthcare copayments	€0	€100 / €200 (c)	€0

Notes: (a) With a maximum of 8 sessions covered annually. (b) With a maximum of 5 sessions covered annually. (c) €100 per 100 minutes of treatment capped at €200 annually.

6.4. Data

This study utilizes proprietary anonymized claims data from a sample of individuals with a basic health insurance from a Dutch health insurer to analyze the number of mental health care treatments. Individuals in our sample that were not insured with this insurer for the entire period between 1 January 2011 and 31 December 2013 have been excluded in order to form an unvarying cohort. Individuals that made use of crisis treatments have been excluded from this sample as well, because such treatments were excluded from copayments.

In this way we created a cohort of 324,675 continuously enrolled individuals. Of these 78 percent were adults (≥18 years), 18 percent non-adults and 4 percent turned 18 during the period examined. This latter group has been excluded from further analysis, since, by turning 18, its individuals shifted from the control group to the treatment group during the period analyzed. The adult group consisted of 46 percent male and 54 percent female and for non-adults there was a 50/50 division. Subsequently, we estimated aggregated socioeconomic status scores (SES-scores)[108] of all individuals by linking their four-digit zip codes[109] to SES-score data of The Netherlands Institute for Social Research (2015). Hence, we found average SES-scores slightly below the national average of 2012: -0.12 for non-adults and -0.11 for adults. The aggregated SES-scores were then used to assign the

106 Long-term mental healthcare treatments include psychiatric institutionalizations of at least one year in duration (at least three years in duration as of January 1, 2015).
107 Exemptions were made for crisis treatments, treatments of involuntarily hospitalization and treatments started after so-called interference care, in which social workers try to persuade worrisome healthcare avoiders to obtain the healthcare services they need.
108 These aggregated neighborhood SES-scores are based on four neighborhood characteristics: average income, percentage of inhabitants with a low income (less than €9,250 annually converted to Dutch price levels of 2000), percentage of low educated inhabitants (highest level of completed education is primary education, pre-vocational education (VMBO) or lower vocational education (MBO-1) and percentage of inhabitants without a job. The SES-scores reflect deviations from the national average over the years 1998- 2014.
109 Dutch zip codes consist of four numbers and two letters (e.g., 1000 AA) in which the numbers indicate a neighborhood or village and the letters indicate one or sometimes multiple streets within this area.

insureds in our sample to a quintile, based on SES-scores in the entire Dutch population. The distribution of individuals from our sample across these SES-quintiles is summarized in Table 6.A1 of Appendix A. Finally, we verified that changes in numbers of primary and secondary mental health care visits within our sample are comparable to national trends (NZa 2015), signifying the external validity of our study.

To analyze health care utilization, we used so-called diagnosis and treatment combination codes (DBC-codes)[110] and general billing information. Dutch health insurers register health care utilization of their insureds through billing information from health care providers. In these bills, health care providers summarize treatments using DBC-codes.[111] For secondary mental health care, DBC-codes include inter alia start and end dates of treatments, the illness that patients suffered (divided in 15 general diagnosis codes based on DSM-IV) and the total duration of the diagnosis and treatment (in ranges of minutes).[112] For primary mental health care, no DBC-codes exist and billing information only provides health insurers with dates of treatment sessions.

We utilize this data to determine when patients started their mental health care treatment, or initial treatments. For outpatient secondary mental health care initial treatments exclude DBC-codes that signify an extension of the treatment after 365 days. All other secondary treatments are considered initial treatments on the billed starting date. As primary care sessions are billed independently and without further detail, it is often unclear whether a consultation is a follow-up or signifies the start of a new treatment. Considering that on an annual basis five primary care visits are covered by the basic health insurance (one every 2.4 months), we assume primary mental health care sessions to be initial treatments when taking place three or more months after a previous primary care session. These initial treatments are measured per 10,000 insureds per month. The number of initial treatments thus found, for both types of mental health care are roughly normally distributed within years in our sample among both adults and non-adults.

6.5. Methods

To evaluate the impact of copayments on mental health care utilization, we analyze changes of the monthly number of initial mental health treatments in our sample for both adults who faced changes in copayments and non-adults who did not face such changes. All analyses are performed using IBM Statistical Package for the Social Sciences (SPSS) version 23.0 for Windows. First, we perform paired *t*-tests for the number of monthly initial treatments between the years 2011 and 2012 and 2012 and 2013 independently for both initial primary and secondary mental health care among non-adults and among adults. In addition, homogeneity of variance is tested by performing a Levene's test alongside all *t*-tests. These are followed by a difference-in-difference analysis between adults (treatment group) and non-adults (control group) over these two periods of time, using ordinary least squares (OLS) regression. We will do so according to the following equation:

$$Y_{at} = \alpha + \beta_a A + \beta_t T + \beta_{\mathrm{at}} AT + \varepsilon_{at} \qquad (6.1)$$

This equation describes mental health care utilization (in average number of monthly numbers of initial treatments) (Y) as a function of adulthood (A) (minor = 0, adult = 1), time (T) (2011 = 0, 2012 = 1 or 2012 = 0, 2013 = 1) and time-differential adulthood effects, with error term ε and subject to parameters α and β. Subsequently, we analyze changes in secondary care utilization, by separating secondary mental health care by kind of disorder treated and by duration of the treatment.

110 For a more detailed overview of the system of DBC-codes, see Tan et al. (2010).

111 It is important to consider that relying on data provided by healthcare providers has two consequences. First, around 66 percent of all patients with a mental condition do not receive any treatment (De Graaf et al. 2012). This group is not included in such data. Second, to an extent healthcare providers have opportunities for upcoding, hence the DBC-codes can moderately deviate from the actual situation (Steinbusch et al. 2007).

112 In the period studied, treatment duration was not reported directly. Ranges of total duration of the diagnosis and treatment could be inferred from the reported tariffs. For example, a fee of 3,297 euro could be matched to a treatment duration between 1,800 and 3,000 minutes.

We expect to find significant changes in utilization for adults in secondary mental health care, while such changes are expected to be absent among non-adults. Although, non-adults and adults are not completely similar groups, there is no reason to believe their mental health care utilization trends are not similar ceteris paribus. The hypothesized differential utilization trend would hence be attributable to the introduction of copayments for adults only. We also expect some impact of the copayments for primary care. Possibly, these changes are smaller than in secondary mental health care as the increase of copayments in primary care is smaller. On the other hand, illnesses treated in primary care are less serious than those treated in secondary care and are thus presumably easier to forego.

Second, we zoom in further on these effects by comparing the number of monthly initial mental health care treatments with the annual mean. Subsequently, we compare this with the annual standard error in order to analyze anticipation effects. Lack of data from earlier years, as well as converse effects of the introduction and repeal of copayments prevent a more sophisticated analysis, correcting for seasonality and annual trends. As anticipatory behavior presupposes awareness of the policy changes among the population, we have also tried to evaluate levels of awareness. Appendix 6.B gives an overview of the utilization of related search terms in Google and links this to events surrounding the development of the new deductible policy and its repeal.

Third, we will analyze to what extent differential effects of copayments exist between men and women and between different SES-quintiles. To do so, we estimate the following equations:

(6.2) $$Y_{gt} = \alpha + \beta_g G + \beta_t T + \beta_{gt} GT + \varepsilon_{gt}$$

(6.3) $$Y_{gt} = \alpha + \beta_s Ses + \beta_t T + \beta_{st} SesT + \varepsilon_{st}$$

These equations describe Y in a similar way as equation 6.1 and as a function of: (6.2) gender (G) (male = 0, female = 1), time (T) and time-differential gender effects; and: (6.3) as a function of SES (SES-quintile A = 0, SES-quintile B = 1), time, and time-differential SES-quintile effects respectively. We will employ an ordinary least squares regression accordingly to estimate regression coefficients between men and women as well as regression coefficient between all pairs of SES-quintiles.

6.6. Results

Paired *t*-tests show that the monthly number of initial secondary treatments for adults differs significantly between consecutive years in the period 2011-2013. Results of these tests are summarized in Table 6.2. In 2012, the number of initial secondary treatments per 10,000 insureds dropped with 11.72 initial treatments (35 percent), compared to 2011 ($p <$ 0.01). As hypothesized, no significant changes are found for mental health care utilization among non-adults. Neither are significant changes in initial primary treatments utilization detected among adults; *t*-tests show only small and non-significant decreases in initial primary visits between 2011- 2012 and 2012-2013. These results are robust and hold when the number of initial treatments is measured per week or per two weeks instead of per month. The variation in monthly number of initial treatments moreover satisfies homoscedasticity.[113] A difference-in-difference analysis of the outpatient secondary mental health care utilization of adults and non-adults over the same periods of time confirms these results. This analysis reveals a significant (p < 0.01) time-differential utilization change between adults and non-adults in 2012 as compared to 2011 (Table 6.3).

113 Levene's tests (Levene 1960) have been performed alongside all t-tests and found no heteroscedasticity between any pair unless stated differently.

Table 6.2 Paired *t*-tests for monthly initial mental healthcare treatments between consecutive years

Years by type of care		adults			non-adults		
		mean dif.	*t*-value	*p*-value	mean dif.	*t*-value	*p*-value
Primary care	2011-2012	-0.85	-0.95	0.36	0.11	0.48	0.64
	2012-2013	-1.06	-1.50	0.15	-0.21	-0.76	0.45
Secondary care	2011-2012	-11.72	-9.65	0.00**	0.26	0.60	0.56
	2012- 2013	1.44	1.47	0.14	-0.24	-0.49	0.63

Note: $^{*}p < 0.05$ $^{**}p < 0.01$.

Table 6.3 Standardized coefficients for average number of monthly initial secondary mental healthcare treatments after OLS-regression

	2011-2012		2012-2013	
	$\hat{\beta}$	*p*-value	$\hat{\beta}$	*p*-value
Adulthood (A)	1.16	0.00**	0.98	0.00**
Time (T)	0.00	0.99	-0.08	0.86
$A \times T$	-0.36	0.00**	0.01	0.92

Note: $^{*}p < 0.05$ $^{**}p < 0.01$.

Table 6.4 Paired *t*-tests for monthly initial secondary mental healthcare treatments by diagnosis code between 2011 and 2012

Diagnosis code	mean dif.	*t*-value	*p*-value
Unknown diagnoses	-8.79	-17.88	0.00**
Other disorders in childhood	0.02	1.50	0.13
Pervasive developmental disorders	-0.13	-1.28	0.22
Attention deficit disorders and behavioral disorders	-0.14	-1.63	0.12
Group rest diagnoses	-1.56	-15.21	0.00**
Adjustment disorders	-1.97	-6.28	0.00**[a]
Other conditions that may be a cause for concern	-1.39	-7.18	0.00**
Delirium, dementia and amnestic and other cognitive disorders	-0.05	-0.83	0.42
Alcohol-related disorders	-0.31	-4.94	0.00**
Other disorders related to an agent	-0.10	-1.19	0.24
Schizophrenia and other psychotic disorders	-0.10	-0.99	0.33
Depressive disorders	0.81	1.63	0.12
Bipolar and other mood disorders	0.05	0.90	0.38
Anxiety disorders	1.09	1.35	0.19
Personality disorders	0.26	0.86	0.40

Notes: * $p < 0.05$, ** $p < 0.01$. (a) A Levene's test found heteroscedasticity of variation.

Focusing on the significant decrease in secondary care utilization among adults in 2012, results display that utilization decreased across many of the existing 15 diagnosis codes. Table 6.4 shows *t*-tests performed on the monthly number of initial treatments by diagnosis code between 2011 and 2012. The results demonstrate that the relatively strongest decreases in treatment utilization can be found among "vague" diagnosis codes: unknown diagnoses, group rest diagnoses[114] and other conditions that may be a cause for concern. Additionally, the utilization of treatments for adjustment disorders seems to have evaporated almost completely after the removal of these disorders from the basic health insurance benefits package.[115] Moreover, treatments for alcohol-related disorders also decreased significantly, highlighting the price responsiveness of these treatments.

Distinguishing by treatment duration, significant and substantial decreases are found for short treatment durations between 2011 and 2012 as well as significant increases in treatments of the shortest and the longest duration in 2013. These results are summarized in Table 6.5. Notably, when separated by duration, in 2013 we find significant increases in utilization of treatments of 0-250 minutes and ≥6,000 minutes in duration, while in general there has been no significant increase in initial secondary treatments. Still, the increase in 2013 for initial secondary treatments of 0-250 minutes of 0.75 per 10,000 insureds does not outweigh the 2012 decrease of 4.08 treatments. Finally, it is important to note that treatments of shorter duration are overrepresented among "vague" diagnosis codes. Hence, decreases in treatment utilization seem concentrated among treatments with "vague" diagnosis codes, treatments of short duration and among treatments that are both of short duration and with a "vague" diagnosis code.

Table 6.5 Paired *t*-tests of monthly initial secondary mental healthcare treatments by duration

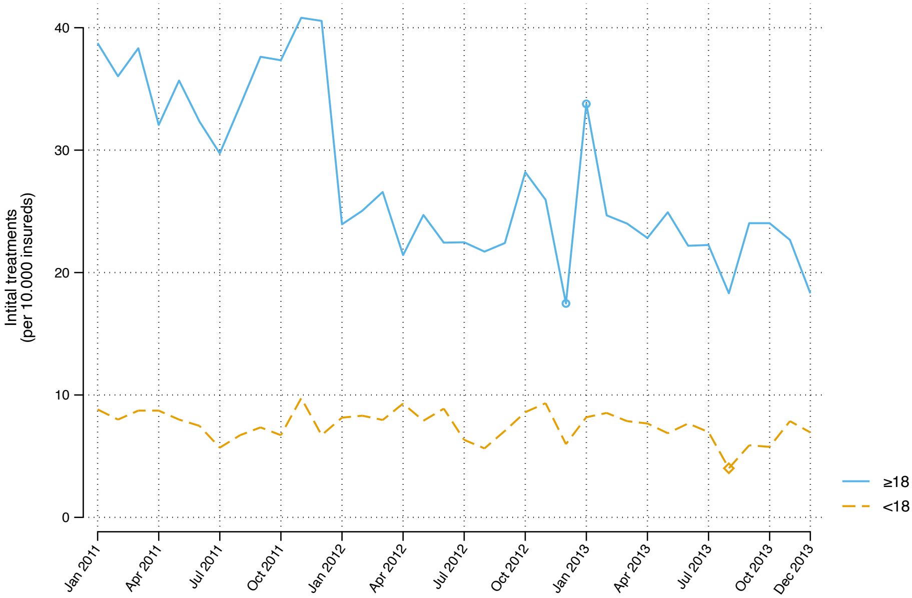
Treatment duration (in minutes)	2011-2012			2012-2013		
	mean dif.	*t*-value	*p*-value	mean dif.	*t*-value	*p*-value
0-250	-4.08	-16.60	0.00**	0.75	3.47	0.00**
250-1,800	-10.62	-9.84	0.00**	0.08	0.07	0.95
1,800-6,000	0.20	0.53	0.50	0.76	1.94	0.07
≥6,000	0.04	0.70	0.49	0.18	2.29	0.03*

Note: * $p < 0.05$, ** $p < 0.01$.

Concerning anticipatory behavior, Figure 6.1 reveals significant deviations from the annual mean of monthly initial secondary treatments among adults at two points in time: in December 2012 and in January 2013. Among non-adults the only significant deviation from an annual mean is found in August 2013. This deviation seems to signify an annually recurring decrease in utilization in July and August that is especially prevalent among non-adults: the summer break. In addition, we find a non-significant increase in initial secondary treatments after the announcement of copayments in June 2011 until the introduction of copayments in January 2012. This increase bears similarities with our proxy for awareness of the introduction of copayment as summarized in Appendix 6.B. Splitting these results by treatment duration, we find that for treatments of 250-1,800 minutes there was a significant negative deviation in December 2012, and a significant positive deviation in January 2013. For treatments of 1,800-6,000 minutes in duration we find a significant positive deviation in January 2013 and a negative deviation in December 2013. No other significant deviations from the annual means have been discovered. Hence, anticipation effects appear to be concentrated among treatments of moderate duration.

114 Group rest diagnoses include DSM-IV diagnoses that have not been assigned separate diagnosis codes such as disorders of impulse control, dissociative disorders and sexual and gender identity disorders.
115 Exclusion of adjustment disorders from the overall analyses summarized in Table 6.2 and Table 6.3 did not alter the interpretation of our findings.

Figure 6.1 Monthly initial secondary mental health care treatments (per 10,000 insureds)



Note: Circles (diamonds) indicate that the monthly number of initial treatments deviates two or more standard errors from the annual mean for ≥18 (<18).

Table 6.6 Standardized coefficients for average number of monthly initial secondary mental health care treatments after OLS-regression

	2011-2012		2012-2013	
	$\hat{\beta}$	***p*-value**	$\hat{\beta}$	***p*-value**
Gender (G)	0.92	0.00**	0.63	0.00**
Time (T)	-0.37	0.00**	-0.21	0.84
$G \times T$	-0.40	0.00**	0.20	0.84

Note: * $p < 0.05$, ** $p < 0.01$.

As for time-differential gender effects, we find that women in general have higher levels of initial secondary treatments, but that these levels decreased significantly more than those of men from 2011 to 2012 (Table 6.6). Hence, the introduction of copayments has decreased mental health care utilization among men, but did so more strongly for women, nearly equalizing the level of treatment seeking in both groups. Thus, copayments did not aggravate existing treatment inequalities between men and women. Rather, such treatment inequalities seem to have diminished in 2012, as especially women, who had previously been more likely to seek treatment, showed a larger reduction in health care utilization (38 versus 30 percent).

Examining time-differential effects between pairs of SES-quintiles, we find no indications of different changes of health care utilization between the SES-quintiles. All SES-quintiles show a mental health care utilization level of 37-44 initial treatments per 10,000 insureds in 2011. In 2012 this dropped to 24-29 initial treatments, with decreases in health care utilization among different SES-quintiles varying from 32 percent for the lowest quintile to 35-36 percent for all other quintiles. Similarly, the analyses does not reveal significant time-differential effects between pairs of SES-quintiles. Possibly, these findings are impacted by the use of aggregated SES-scores to estimate individual SES-scores.

6.7. Conclusion and discussion

In this study, we examined the effects of changes in cost sharing in both primary and secondary mental health care in the Netherlands. We capitalized on the exemption of non-adults from copayments to form a control group. We employed *t*-tests and OLS-regressions to evaluate utilization differences among different years, within subgroups and between various treatments. This adds to the existing copayment literature by estimating demand response without selection effects and with a natural control group.

First, our results show that the introduction of a secondary mental health care copayment of €200 was followed by a 35 percent decrease in initial treatments among adults, without selection effects. A similar decrease was absent among non-adults. The impact of the copayments was strongest among treatments of short duration and treatments with "vague" diagnoses. This provides further evidence that the way in which copayments affect health care consumption depends partially on the necessity of care. However, we find no changes in primary health care utilization for milder care needs. Presumably, this is because primary mental health care copayments were already in place and were only increased with €10 per visit in 2012.

Second, our findings confirm the existence of anticipatory behavior; in line with earlier research the data showed increased mental health care utilization prior to the introduction of copayments in 2012 and significantly reduced initial treatments prior to the repeal of copayments in 2013. This implies that the demand response excluding anticipation effects is lower than 35 percent. The anticipation effects are concentrated among treatments of relatively short duration, suggesting that anticipatory behavior is strongest where general utilization effects are strongest and that both effects vary with the necessity of care.

Third, we find some evidence for a differential impact of copayments: mental health care utilization decreased significantly more among women (38 percent) than among men (30 percent). We find no significant differences in utilization changes between SES-quintiles. Possibly, this is due to the use of aggregated SES-scores based on zip code to estimate individual SES-scores. Still, our findings show lower decreases in health care utilization among groups that have been identified as underutilizing mental health care by existing research. Mental health care utilization decreased significantly less among men than among women and less – albeit not significantly – among the lowest SES-quintile compared to other SES-quintiles.

It is important to be aware of the limitations of our study when interpreting the results. We used data from one single Dutch health insurer. Although utilization trends of its insureds are in line with national trends, it is possible that this has influenced our results. Furthermore, a general assumption of studies relying on health care provider data is that providers register treatments accurately and in good faith. In addition, our analysis evaluates mental health care utilization trends by various partitions independently. As we have noted, some correlation exists between these variables and should be taken into account when interpreting our findings. Furthermore, we assumed that differences in mental health care utilizations between the different years analyzed are attributable to the introduction and repeal of copayments. Yet, the increases in the annual mandatory deductible may also have had a downward effect on the demand for mental health care by adults in 2012 and 2013. This implies that the impact of the new copayment scheme in 2012 has probably been overestimated. The higher deductible could also partially explain why mental health care utilization has not returned to its pre-2012 level after the repeal of copayments in 2013.

Our results have important implications for policy makers both in the Netherlands and in other countries. We find that copayments for secondary mental health significant have a strong impact on mental health care utilization. The utilization effects, moreover, are unevenly distributed among the population, indicating that implementing copayments may change the distribution of mental health across a population. At the same time, the existence of anticipatory behavior shows that policy changes concerning health insurance coverage should be carefully implemented. Finally, this research has not focused specifically on evaluating costs and benefits of the implemented policy nor on its mental health effects or (potential) long-term effects, which hence remain fruitful areas for future research.

6.8. Appenidces

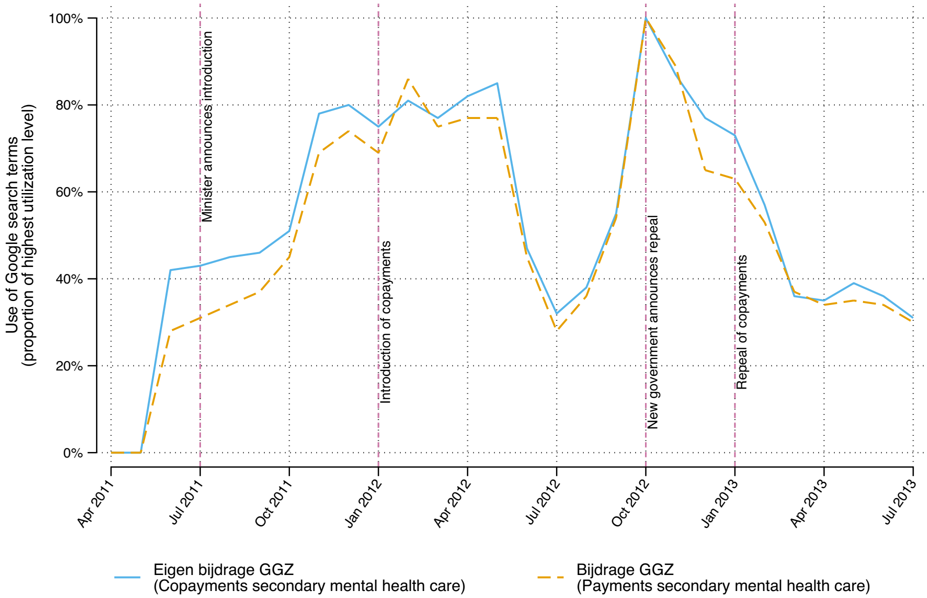
A. SES-quintiles

Table 6.A1 Overview of the distribution of the sample over population SES-quintiles

SES-quintiles	SES-range	Percentage of total sample
0-20%	-5.93--0.48	29.3%
20-40%	-0.49-0.11	23.7%
40-60%	0.12-0.52	13.1%
60-80%	0.53-0.97	14.5%
80-100%	0.98-2.93	19.4%

B. Google search terms

Figure 6.B1 Use of copayment-related search terms in Google and matching events between April 2011 and June 2013



Note: Data for search term utilization has been retrieved from Google Trends (n.d.).

7

Conclusion and discussions

7. Conclusion and discussion

7.1. Introduction

Insurance plays a crucial role in providing access to care and in mitigating financial risks of care needs. This thesis has sought to contribute to a better understanding of the decisions that people make about purchasing and using insurance for health care services. Chapters 2-5 have examined the market for long-term care insurance. They have provided an overview of the barriers for taking-out long-term care insurance and have further examined the impact of adverse selection, nonstandard preferences and misunderstanding that this review has brought up. Chapter 6 has analyzed changes in the decision to seek mental health care when insurance coverage is reduced by the introduction of a copayment. This chapter summarizes the main findings of the preceding chapters one by one. Then, it discusses implications for policy makers and insurance markets.

7.2. Main findings

7.2.1. Insurance puzzles: long-term care insurance and life annuities

Chapter 2 surveys the literature on demand for long-term care insurance on which Chapters 3-5 build. We perform a systematic literature review to examine the puzzling underinsurance in markets for long-term care insurance and life annuities. The systematic search found 3,945 unique studies and after careful selection based on predefined criteria, the findings of 187 studies were used. The integration of these studies shows that the explanations for the low demand for both types of insurance are similar.

Some of these explanations fit well within the predictions of expected utility theory. First, public insurance schemes may crowd out demand for insurance among eligible individuals. Second, insurance markets may suffer from adverse selection as individuals that take-out insurance typically belief to be bad risks. Other explanations, however, suggest that preferences are broader than those defined by expected utility. Particularly, they find that lack of trust in insurers may reduce insurance demand. Finally, people may find decisions regarding these insurance products difficult and consequently fail to purchase them. In this regard, the low uptake among individuals with low levels of financial literacy is particularly striking.

7.2.2. Predicting lifetime nursing home use

In Chapter 3, we further analyze the potential for adverse selection in the market for long-term care insurance. Though individuals hold private information on the short run (i.e., 5 years) it is unknown whether individuals can predict nursing home use further ahead. Long-term care insurance, however, is typically bought around the age of 60, which for most individuals is much longer than 5 years before nursing home entry. We therefore examine whether beliefs about the lifetime risk of nursing home entry elicited before the age of 65 are predictive of nursing home entry.

We use data from the Health and Retirement Survey (HRS), a biannual and longitudinal survey held by the University of Michigan since 1992. The rich survey data contains information on health, wealth, and care use. When respondents die, interviews are held with people knowledgeable of their finances and health. As such, the HRS provides a nearly complete overview of the health and wealth of a representative sample of the US population around and after retirement. We exploit that since 1996 the HRS has asked all new respondents under the age of 65 to estimate their lifetime probability of nursing home use. We match this with observed nursing home use over up to 20 years (until 2016). We find that both are weakly correlated.

However, the data is right censored because many participants are still alive when we last observe them. We gauge the bias that this introduces in three ways. First, we analyze the predictive power of lifetime probabilities among deceased individuals only. Second, we examine the correlation of lifetime probabilities of nursing home use with survival beyond the last observed interview. Third, we match surviving respondents to respondents from on older HRS cohort based on gender, age, nursing home use over the last two years and subjective probabilities of nursing home entry within five years. Results all indicate that right censoring biases our estimates downwards. Subjective lifetime probabilities of nursing home entry are more predictive among deceased respondents than among survivors, are highly predictive of survival, and are more predictive when imputing unobserved future nursing home use.

When we control for characteristics that insurers may use in underwriting, we find that subjective lifetime probabilities of nursing home use do no longer correlate with observed nursing home. However, even conditionally on underwriting criteria the subjective lifetime probabilities correlate strongly with survival and with later short-term subjective short-term probabilities. This suggest that even over time horizons of decades, people may be better able to assess whether they are a good or bad risk than insurers and leaves at least some scope for adverse selection to occur after the observed 20 years.

7.2.3. Ambiguous nonperformance risks

In Chapter 4 we analyze the impact of a type of nonstandard preference on insurance demand. Our literature review revealed that trust is an important driver of insurance demand. Analogously, economic experiments have shown that people strongly dislike insurance products that has a known probability of not paying out. In practice, however, such probabilities of nonperformance are unknown. We hold an incentivized lab experiment with 117 participants facing substantial losses that are deducted from a salient show-up fee of €25. In this experiment, participants perform insurance tasks, and we elicit risk and ambiguity preferences. We use this data to both compare insurance demand with known and unknown nonperformance risks and explain insurance demand by nonparametric measures of preferences.

Our results show that, consistent with theoretical predictions, an ambiguous nonperformance risk leads to a further reduction in insurance demand compared to a known nonperformance risk. Even so, a binary measure of ambiguity aversion could not explain this effect. We have two – not mutually exclusive – explanations for this. Fist, our measure of ambiguity attitudes is consistent with the theoretical literature but may be too restricted to capture non-uniform ambiguity preferences. Second, the elicited preferences may in general not be well-suited to explain other decisions. After all, our findings also show that individuals prefer insuring against large probabilities over insuring against small probabilities, even though most of them overweigh small probabilities and underweigh large probabilities.

7.2.4. Decision-making abilities and selection in long-term care insurance

In Chapter 5 we examine the impact of misunderstanding on insurance demand. Particularly, we analyze the interaction between decision-making abilities (i.e., education and numeracy) and private information on the market for long-term care insurance. The existence of such interactions has previously been hypothesized. After all, people with greater decision-making abilities might be better able to acquire predictive private information and better able to adjust insurance holding to their private information. We propose an extension of the positive correlation test to detect adverse selection due to the interaction of private information with other characteristics. Just like in Chapter 3, we rely on the HRS (N = 30,000+) to provide information on subjective (short-term) probabilities, insurance holding and health information that closely mirrors the information collected by insurers for underwriting purposes.

Our results show that decision-making abilities on their own drive selection in the market for long-term care insurance. Specifically, we find that insurance holding is higher among more numerate and higher educated individuals. More numerate individuals use less nursing home care because they are unlikely to become cognitively impaired soon, driving advantageous selection. Higher educated individuals are at larger risk of needing nursing home care at all, generating adverse selection. Although many higher educated individuals are also more numerate and cognitively intact, a substantial unconditional adverse selection effect of education remains. When examining interactions, we find that private information of those with greater decision-making abilities is not more predictive of actual nursing home use. However, private information is more strongly correlated with insurance holding among both higher educated and more numerate individuals. Therefore, the interaction between decision-making abilities and private information intensifies selection in the market for long-term care insurance.

7.2.5. Insurance coverage and demand for mental health care

Chapter 6 analyzes the impact of the introduction of a new copayment scheme on the use of mental health services in the Netherlands. In 2012, copayments for primary mental health care were doubled from €10 to €20 per visit and copayments of up to €200 annually were introduced for secondary mental health care. Mental health care use may be particularly price sensitive, and we examine this in a setting with mandatory insurance such that estimates of price sensitivity are unaffected by adverse selection.

Using a large, proprietary dataset of a private Dutch health insurer, we create a cohort of more than 300,000 insureds that are continuously enrolled between the 1st of January 2011 and 31st of December 2013. We capitalize on the fact that minors (i.e., those under 18 years of age) are exempted from paying copayments and perform a difference-in-differences analysis of mental health care use over this period. In addition, we evaluate which treatments are most affected and whether there are differences in effects of copayments across subgroups within the population.

Our results show that the new copayment scheme substantially reduced utilization of secondary mental health care among adults, whilst secondary mental health care use among minors remained stable. Within secondary mental health care this reduction has mainly impacted treatments of shorter duration. We find no evidence that the copayment scheme impacted the use of primary mental health care, probably because the increase in copayments for primary mental health care was relatively small. Price responses have, however, been heterogeneous. First, we find evidence of anticipatory behavior increasing the utilization of shorter treatments prior to the introduction of the new copayment scheme. Second, we find evidence that the decrease in utilization was larger among women than among men but found no evidence of differences by socioeconomic status.

7.3. Implications

What can we learn from these findings? Insurance markets, and those for long-term care and mental health care in particular, are imperfect. This thesis analyzes several of these imperfections and offers insights that may aid policymakers in their attempts to alleviate them.

The results highlight that, in absence of individual mandates or comprehensive public insurance schemes, insurance coverage for long-term care is distributed unequally across the population. In so far as that reflects an active choice to substitute for private insurance or mirrors risk preferences, it may not require any intervention. Even so, regulation can help to shape products that are more appealing to consumers and thus prevent governments – either directly or through public insurance programs – from footing the bill of future care costs. Our findings show that reducing nonperformance ambiguity could present such an opportunity to increase the uptake of insurance products in general, and long-term care insurance and other long-term insurance products in particular. Such nonperformance ambiguity remains a highly topical issue. In the Netherlands, for example, a life insurer went bankrupt despite the presence of stringent solvency regulations, leaving about 70,000 customers with seriously discounted (till 30 percent) insurance benefits (Zandbergen 2021). Reducing this ambiguity through, for example, a common guarantee fund that insures against unlikely insurer bankruptcies could help increase insurance demand. In addition, regulators may require insurers to guarantee inflation protection to ensure reasonable payouts in case of an insured event in the far future.

To the extent that lower uptake reflects adverse selection or limited rationality, it is a product of underlying inequalities – both in health or longevity and in capabilities – and may warrant policy interventions. Until now, much policy attention has been focused on increasing risk-awareness and empowering individuals to make the right insurance decisions. Findings of this thesis suggest that such interventions may in-fact have detrimental effects. After all, empowering individuals to make insurance decisions through increasing decision-making skills may particularly stimulate insurance uptake among those who are bad risks and thus aggravate adverse selection. As such, increasing decision-making abilities may reduce inequalities in insurance coverage by capabilities, but increase inequalities by health. That individuals may hold private information over longer periods of time than previously examined, only further aggravates such issues of selection. If the goal is to better protect those with lower decision-making abilities against financial consequences of health risks, without increasing adverse selection, this may only be attained by limiting the scope of voluntary insurance decisions, for example through individual mandates or other coverage requirements.

Even so, expanding insurance coverage is not without risk for health care expenditures. After all, insurance coverage may lead to moral hazard. Policy makers have typically sought to curb moral hazard by introducing copayments. Our results show that copayments substantially decrease mental health care utilization, indicating that mental health care is particularly susceptible to moral hazard. This suggests that expanding insurance coverage to forms of care that are sensitive to moral hazard may substantially increase health care expenditures. Yet, copayments may also change the distribution of care across the population. Even though we find no evidence of differences in demand responses by socioeconomic status, we do find that copayments have reduced mental health care utilization more strongly among women then among men. This raises the question whether the observed price response reflects individual preferences for health care and health only and highlights the importance of a careful trade-off between risk protection and efficiency when introducing or raising copayments for mental health care. Policy makers who aim to reduce moral hazard and protect access to mental health care, may therefore exempt vulnerable groups from having to pay for mental health care out of their own pocket.

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Summary

Summary

Insurance is pivotal in financing health care services. Yet, standard economic models do not fully explain observed behavior in real-life insurance markets. This thesis aims to add to the understanding of insurance decisions. To that end, this thesis analyzes consumer behavior on the market for long-term care insurance and insured mental health care, where deviations from standard economic predictions may be particularly apparent.

Chapter 1 discusses what we know of consumer decisions in insurance markets. It explains why economists study insurance decisions, overviews the standard economic framework to understand them and discusses the related empirical findings. Next, the chapter introduces the behavioral economic concepts that this thesis employs to better understand insurance decisions.

Chapter 2 reviews the scientific literature on consumer decisions for underinsurance puzzles: of long-term care insurance and of life annuities. Integration of both theoretical and empirical research shows that the take-out of long-term care insurance and life annuities is hindered by four comparable mechanisms. First, public insurance substitutes for these products. Second, both insurance markets suffer from adverse selection, where bad risks with large probabilities of entering a nursing home or growing old are more likely to hold long-term care insurance or life annuities. Third, individual preferences deviate from standard expected utility models. Fourth, insurance products are ill understood by consumers.

Chapter 3 further examines the potential of adverse selection on the market for long-term care insurance. Because of data limitations, research on long-term care insurance has previously only considered adverse selection over relatively short follow-up periods. Sophisticated imputation methods show that subjective lifetime probabilities of nursing home entry, like subjective short-term probabilities, are predictive of actual nursing entries. Moreover, information that is unknown to insurers, remains predictive of survival and beliefs up to 20 years later. This indicates that subjective probabilities may generate adverse selection over far greater timespans than previously found.

Chapter 4 dives deeper into the role of nonstandard preferences in insurance decisions. Insurance products normally encompass a risk that valid claims are not reimbursed. A well-known finding is that individuals have a strong dislike of such nonperformance risks that cannot be explained by standard economic risk preferences. We held a lab experiment to compare insurance demand for products with objectively known and unknown nonperformance probabilities. Results show that ambiguity of nonperformance probabilities further reduces insurance demand. Even so, this decrease in insurance demand cannot be explained by a simple measure of ambiguity aversion.

Chapter 5 analyzes differences in decision-making abilities in long-term care insurance decisions. Holding of insurance products varies by education and numeracy, presumably because the long-term care insurance market is particularly difficult to navigate. This chapter shows that these decision-making abilities are also correlated with long-term care use and thus generate selection on this market. Furthermore, it is shown that decision-making abilities may reinforce adverse selection from private information: those with greater decision-making abilities are more likely to hold insurance when they have private information of being a bad risk.

Chapter 6 evaluates the impact of the introduction of copayments in mental health care in the Netherlands. Copayments may hit demand for mental healthcare particularly hard as individuals suffering from mental illness may be even more likely to deviate from self-interested behavior (Frank & McGuire 2000). We find that the new copayment scheme substantially decreased mental health care utilization. This decrease was concentrated among treatments with short durations. In addition, we find some heterogeneity in demand responses to the new copayment scheme by gender, but not by socioeconomic status

Chapter 7 concludes by taking together the main research findings and providing policy recommendations.

Samenvatting

Samenvatting

Verzekeringen spelen een belangrijke rol in het financieren van zorg. Toch verklaren standaard economische modellen het gedrag op verzekeringsmarkten niet volledig. Dit proefschrift heeft daarom tot doel het begrip van verzekeringsbeslissingen te vergroten. Daarvoor analyseert dit proefschrift consumentengedrag op de markt voor ouderenzorgverzekeringen en in de verzekerde geestelijke gezondheidszorg. Juist op deze markten kunnen afwijkingen van standaard economische voorspellingen bijzonder aanwezig zijn.

Hoofdstuk 1 bespreekt wat we weten over consumentenbeslissingen in verzekeringsmarkten. Het legt uit waarom economen verzekeringsbeslissingen bestuderen, geeft een overzicht van het standaard economische raamwerk om ze te begrijpen en bespreekt de gerelateerde empirische bevindingen. Vervolgens introduceert het hoofdstuk de gedragseconomische concepten die in dit proefschrift worden gebruikt om verzekeringsbeslissingen beter te begrijpen.

Hoofdstuk 2 geeft een overzicht van de wetenschappelijke literatuur over consumentenbeslissingen voor onderverzekeringspuzzels van ouderenzorgverzekeringen en lijfrentes. Tezamen laten theoretisch en empirisch onderzoek zien dat het afsluiten van ouderenzorgverzekeringen en lijfrentes wordt belemmerd door vier vergelijkbare mechanismen. Ten eerste worden deze producten verdrongen door volksverzekeringen. Ten tweede lijden beide verzekeringsmarkten onder adverse selectie. Daarbij bezitten mensen met een grote kans om naar een verpleeghuis te gaan of oud te worden ook vaker ouderenzorgverzekeringen of lijfrentes. Ten derde wijken individuele voorkeuren af van standaard economische modellen. Ten vierde worden verzekeringsproducten slecht begrepen door consumenten.

Hoofdstuk 3 gaat verder in op het risico van adverse selectie op de markt voor ouderenzorgverzekeringen. Vanwege databeperkingen heeft onderzoek naar adverse selectie bij ouderenzorgverzekeringen zich tot nu toe gericht op relatief korte periodes. Geavanceerde imputatiemethoden laten zien dat schattingen van de kans op opname in een verpleeghuis gedurende de levensloop, net als inschattingen voor opnames op de kortere periodes, daadwerkelijke opnames in een verpleeghuis kunnen voorspellen. Bovendien blijft informatie die niet bekend is bij verzekeraars tot 20 jaar later voorspellend. Voor zowel de kans op overleven als voor latere schattingen van de kans op verpleeghuiszorg. Dit wijst erop dat subjectieve kansen adverse selectie kunnen veroorzaken over veel grotere tijdspannes dan eerder gevonden.

Hoofdstuk 4 gaat dieper in op de rol van niet-standaard voorkeuren bij verzekeringsbeslissingen. Verzekeringsproducten brengen normaal gesproken een risico met zich mee dat geldige claims niet worden vergoed. Een bekende bevinding is dat individuen een sterke afkeer hebben van dergelijke risico's. Deze afkeer kan niet worden verklaard door standaard economische risicovoorkeuren. We hebben een laboratoriumexperiment gehouden om de verzekeringsvraag te vergelijken tussen producten met objectief bekende en onbekende kansen op niet uitbetalen. De resultaten tonen aan dat onzekerheid van de kans op niet uitbetalen de verzekeringsvraag verder vermindert. Toch kan deze afname van de vraag naar verzekeringen niet worden verklaard door een eenvoudige maatstaf van onzekerheidsvoorkeuren.

Hoofdstuk 5 analyseert verschillen in beslisvermogen bij keuzes voor ouderenzorgverzekeringen. Het bezit van verzekeringsproducten verschilt naar opleiding en numerieke vaardigheden, vermoedelijk omdat de markt voor ouderen zorgverzekeringen bijzonder ingewikkeld is. Dit hoofdstuk laat zien dat beslisvermogen ook samenhangt met gebruik van ouderenzorg en zo leidt tot risicoselectie op deze markt. Verder laten we zien dat beslisvermogen adverse selectie kan versterken: mensen met een groter beslisvermogen, hebben namelijk een grotere kans om een verzekering af te sluiten als ze informatie hebben een slecht risico te zijn.

Hoofdstuk 6 evalueert de introductie van eigen bijdragen in de geestelijke gezondheidszorg in Nederland. Eigen betalingen kunnen de vraag naar geestelijke gezondheidszorg bijzonder hard treffen, omdat mensen met een psychische aandoening nog meer geneigd zijn af te wijken van hun eigenbelang (Frank & McGuire 2000). Deze evaluatie laat zien dat de nieuwe eigen bijdrage het gebruik van de geestelijke gezondheidszorg inderdaad aanzienlijk heeft verminderd. Deze afname was geconcentreerd bij behandelingen met een korte duur. Bovendien vinden we verschillen in de reactie op de nieuwe eigen bijdrage naar geslacht, maar niet naar sociaaleconomische status

Hoofdstuk 7 besluit met het samenbrengen van de belangrijkste onderzoeksresultaten en het geven van beleidsaanbevelingen.

Acknowledgements

Acknowledgements

I could not have written this PhD thesis without the many people who have helped me along the way. I therefore want to express my gratitude to those who have contributed, directly or indirectly, to this thesis.

First, my promotors Erik Schut en Han Bleichrodt. I'm grateful for the funds that you have raised for this PhD position and the faith that you have put in me to fulfill this position. Erik, your tranquility, and overview have truly helped during the difficult periods that are inherent to a PhD. With your constructive feedback and questions, you have always managed to steer me in the right direction. Mostly, however, I want to thank you for your genuine interest in others, which has made me feel supported throughout my PhD. Han, I have learned a great deal from our discussions. I want to thank you for stimulating me to find my own path in academia.

This thesis would not have been the same without the valuable contributions of my coauthors Paul van Bruggen and René van Vliet. Paul, our discussions on the (interpretation of) the literature and the design of our lab experiment were very valuable. Thank you for your diligence and patience. René, without the master thesis that I have written under your supervision, I might never have started this PhD. Thank you for challenging and guiding me along the way.

This thesis has benefited from the help of many others. I would like to thank Bram Wouterse, David Dicks, John Hsu, Lisa Voois, Marianne Tenand, Owen O'Donnell, Raf van Gestel, Richard Peter and Wynand van de Ven for their helpful comments on earlier versions of various chapters in this thesis. I would like to thank Bryan McGarry, Casper van Ewijk, David Grabowski, Joan-Costa Font and Wichor Bramer for their help in the systematic literature review in Chapter 2. I would also like to thank Aurelien Baillon for is help in designing and Alice Havrileck for her support in running the lab experiment that provided the data for Chapter 4. Finally, I would like to thank Peter Wakker for providing me with a solid introduction to behavioral economics, both through his teaching and through the weekly behavioral economics group meetings.

Finally, this would not be an actual PhD thesis without the doctoral committee. Thank you for the time and effort you have put in evaluating this thesis. I am delighted that you will be acting as my opponents during the defense ceremony.

Other help has been more indirect, but certainly no less important. The bi-weekly meetings of the Erasmus University long-term care group deserve a special mention. Bram Wouterse, Eddy van Doorslaer, Judith Bom, Julien Bergeot, Leonoor Graler, Marianne Tenand, Marlies Bär, Pieter Bakx, Sara Rellstab and Thijs van den Broek, probing new research ideas, discussing early phase research has always been encouraging with you.

Although part of this thesis has, in fact, been written on an attic, it has not been written in solitude. I thank my colleagues for enriching my time at Erasmus University Rotterdam, and at the department of Health Systems and Insurance in particular. A few colleagues deserve a special mention.

I would like to thank those with whom I have taught various courses. Igna Bonfrer, Marco Varkevisser, Marjolein Timmers, Richard van Kleef and Stéphanie van der Geest. Thank you for the smooth collaboration and for your reflections on my teaching experiences and questions.

My fellow board members at young-ESHPM: Eline Linthorst, Frédérique van Krugten, Marthe Stevens, Mathilde Berghout and Stefan Lipman. We have put a lot of energy into organizing workshops, measuring PhD experiences and discussing faculty policies to better PhD-trajectories. I have very much enjoyed this working with you and have learned a great deal from all of you. Marthe, our lunches were always something to look forward to.

The organizing committee of the 7th ESHPM lustrum: Kirti Doekhi, Martijn Felder and Wouter Kleijheeg. Martijn, your enthusiasm is inspiring and ensured that our brainstorms never ran ashore (although we may have gotten adrift occasionally). Kirti and Wouter, thank you for helping me find my way around at ESHPM. Having you around at the start of my PhD has been indispensable.

My officemates: Daniëlle Cattel and Wouter van der Schors. I assume that sharing an office with me has not been easy. Even so, you have never complained about the countless bad jokes, murmurings and questions (both substantive and less substantive) that I have produced over the years. Daniëlle, thank you for your warm personality and candidness. From the very beginning you have made me feel at home at ESHPM. Wouter, I admire your thoughtfulness and spirit. With you around there was always a new coffee to get and amazements to share.

Of course, I would also like to thank my colleagues at CPB Netherlands Bureau for Economic Policy Analysis, and the health care program in particular, for their support during the last phase of my PhD. Anne-Fleur Roos, I count myself lucky to have you as a colleague once again. Thank you for your listening ear and advice.

No thesis acknowledgement is complete without tribute to the paranymphs. Annette, thank you for always sharing your positivity and sparkle. Your creativity is unparalleled and I'm beyond grateful for your help in designing this thesis. Rhea, your down-to-earthness has often helped me put things into perspective. I value that we have grown closer as siblings over the years. I am glad to have you both by my side during the defense of this thesis.

Finally, I want to thank my family. To my in-laws: thank you for always being there for us. Mum and dad, you have always encouraged me to be curious and to learn new things. This thesis certainly shows that was not in vain. Thank you for everything.

Mark, your pancakes have quite literally fueled this thesis, but you have also protected me when my eyes were (again) bigger than my stomach. Thank you for your love and support. Every day, I feel lucky to share my life with you.

Curriculum vitae

Portfolio

Education

PhD in Health Economics
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Publications

Peer-reviewed publications

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Lambregts, T., & Schut, F. (2020). Displaced, disliked and misunderstood: a systematic review of the reasons for low uptake of long-term care insurance and life annuities. *J. Econ Ageing, 7, 1-28.*

Lambregts, T., & van Vliet, R. (2018). The impact of copayments on mental healthcare utilization: a natural experiment. *Eur. J. Health Econ., 19(6), 775-784.*

Professional publications

Bangma, K., van Eekelen, L., van Ewijk, C., Kamminga, K., Koetsier, I., Kortleve, N., ... & Zulkarnain, A. (2021). Toekomst arbeidsmarkt en pensioen: een verkenning voor de langere termijn. Netspar Occasional Paper Series No. 01/2021.

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Lambregts, T., & Schut, F. (2020). Waarom is er zo weinig vraag naar verzekeringen tegen ouderdomsrisico's? Het verzekeringsarchief.

Lambregts, T., & van Vliet, R. (2018). GGZ-gebruik daalt door invoering eigen bijdrage. *Econ. Stat. Ber., 4757*, 20-21.

Teaching experience

Supervisor bachelor theses in health sciences	(ESHPM, 2016-2020)
Supervisor and co-reader master theses in behavioral economics	(ESE, 2017-2018)
Tutor bachelor level statistics in "multivariate analyse"	(ESHPM, 2016-2019)
Supervisor pre-master level statistics in "kwantitatief leeronderzoek"	(ESHPM, 2017)
Tutor bachelor level economics in "algemene economie"	(ESHPM, 2018)
Tutor bachelor level introduction in "de nederlandse gezondheidszorg"	(ESHPM 2018)
Tutor bachelor level economics & statistics in "marktordening in de zorg"	(ESHPM, 2020)

Invited talks and presentations

2019 Erasmus University (ESHPM), Rotterdam; 11th Lowlands Health Economists' Study Group, Almen; SABE/IAREP Conference, Dublin; 46th Seminar of the European Group of Risk and Insurance, Rome; 1st Smarter Choices for Better Health Symposium, Rotterdam.

2018 Netspar International Pension Workshop, Leiden; Erasmus University (ESE), Rotterdam; Vivat, Amstelveen; Netspar Workgroup-day, Amsterdam.

2017 Erasmus University (ESHPM), Rotterdam; 13th Workshop on Mental Health Policy and Economics, Venice.

Training

Academic

Experimental economics	(Tinbergen Institute, 2017)
Risk and rationality	(Tinbergen Institute, 2017)

Didactic

Basic didactics	(Erasmus University, 2017)
Bachelor thesis supervision (intervision)	(Erasmus University, 2017)
Thesis coaching	(Erasmus University, 2018)
Group dynamics	(Erasmus University, 2018)
Teaching tutorials (intervision)	(Erasmus University, 2018)

Professional

Project management for PhDs	(Erasmus University, 2016)
Academic writing	(Erasmus University, 2017)
Doing the literature review	(Erasmus University, 2017)
Influencing effectively	(De Heren van Werk, 2020)

Other activities

Member of the ESHPM activities committee	2016-2017
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Member of the bachelor reform subcommittee "marktordening in de zorg"	2017-2018
Chairman of the ESHPM PhD association yESHPM	2017-2019
Member of the strategic workgroup "fostering collaboration"	2018-2019

About the author

Timo Lambregts (1993) completed a BA. in Chinese Studies (2013), a BSc. (with honors) in Economics, Public Administration and Management (2015), and a MSc. In Health Economics, Policy and Law (2016). He then obtained a PhD position at the Erasmus School of Health Policy and Management (ESHPM) funded by the Research Excellence Initiative of the Erasmus University Rotterdam.

During his PhD, he studied consumer decisions on insurance markets for long-term care and mental health care. His work has been published in several international peer-reviewed journals as well as professional journals and he has presented his research on multiple national and international conferences. In addition, Timo has taught in various bachelor and premaster courses on economics and statistics and supervised multiple bachelor and master theses.

Currently, Timo is working as a scientific researcher at CPB Netherlands Bureau for Economic Policy Analysis. There, he studies the functioning of health care markets and the effects of health care policies.