ANALYZING HIDDEN AND INDIRECT FACTORS FOR RISING HEALTH EXPENDITURE

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Preface

While writing this dissertation as a research assistant at the CINCH-Health Economics Research Center in Essen, I benefited from support by many people and institutions.
I am thankful that I was allowed to use and to benefit from the excellent infrastructure at CINCH and the University of Duisburg-Essen. The professional and supportive environment and many discussions with colleagues were a very valuable input for all chapters of this work. Further, I gratefully acknowledge financial support by the Federal Ministry of Education and Research (Bundesministerium für Bildung und Forschung), the German Research Fund (DFG) and the Fritz Thyssen Foundation. Apart from that, I am also grateful to the Rheinisch-Westfälisches Institut für Wirtschaftsforschung e.V. (RWI) for providing access to data.

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Contents

List of Tables

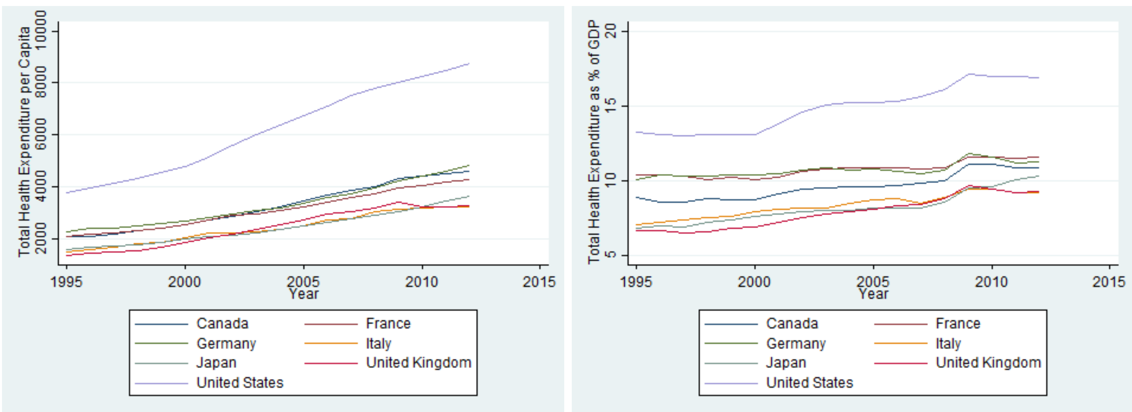
List of Figures

1 Introduction

1.1 The Motivation

Rising health expenditure is a major concern of most industrialized countries. As illustrated in Figure 1.1, not only nominal health expenditure per capita but also health expenditure as a share of gross domestic product (GDP) have risen steadily over the last decades in G7-countries. Among various reasons, this development can be traced back to four factors, that provide the basis for the following analyses. The first and probably most prominent reason is the aging of societies due to the demographic change in industrialized countries. Second, technological progress increases health expenditure. Third, there are trends in awareness for certain diseases that may induce higher health expenditure. And last but not least, inefficient health insurance markets can increase the amount spent on health care and insurances.

Figure 1.1: Development of Health Expenditure in G7 – Countries



(a) Total Health Expenditure per Capita in G7-countries (USD-PPP)

(b) Total Health Expenditure as % of GDP in G7-countries

Own diagram based on data from OECD (2015).

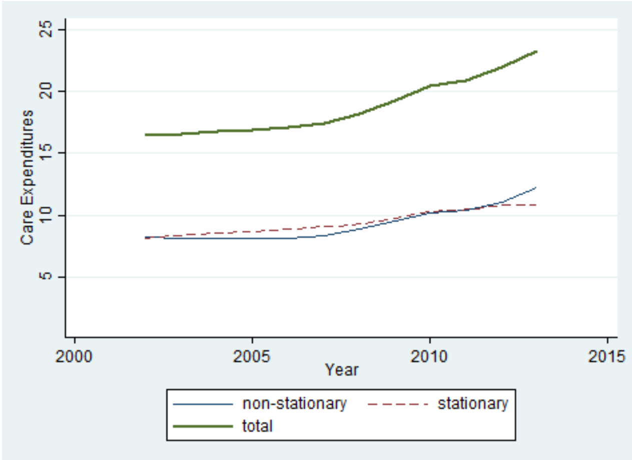
The problems of the demographic change are twofold: (i) In an aging society there are less persons in working age that contribute to social pay-as-you-go insurance systems. This decreases the financial base of social insurances while (ii) the share of non-working (older and retired) persons, who do not contribute but benefit from social insurances, increases. Proceeding on the assumption that health expenditure and age are closely interrelated, aging is often claimed to be of great importance when analyzing rising health expenditure. That is, both, revenue and expenditure side of social insurances is affected by demographic aging.

Although, the direct connection between age and health expenditure and the relative importance of age as determinant of health expenditure is subject to debate in economics (e.g. Zweifel et al., 1999; Felder et al., 2000; Werblow et al., 2007; Felder et al., 2010; Wong et al., 2011; Payne et al., 2007; Karlsson and Klohn, 2014), total health expenditure, which also include expenditure for long-term care facilities and infrastructure for the elderly, are connected to age. The probability of being in need of care increases sharply with age. The German Federal Ministry of Health states that the probability to be in need of care rises from 4.2% for persons aged 60 – 80 to 28.8% for persons older than 80 years[1] (Bundesministerium für Gesundheit, 2014). A large share of health expenditure is spent for elderly persons in need of care. Based on the aforementioned probabilities, the German Federal Ministry of Health predicts the share of persons older than 80 years to be around 14.8% in 2050, which translates to 4.23 million care recipients in 2050 compared to roughly 2.5 million today (Bundesministerium für Gesundheit, 2014). Along with this demographic development, the amount spent for professional care and nursing facilities will increase further. While this instantly increases the direct expenditure for professional care, there is also an indirect effect. Already today, the relatively largest part of care recipients is cared for at home by informal caregivers alone or in cooperation with professional mobile nursing services. In recent years, the relative importance of this type of care provision has even slightly increased, as shown by figure 1.2. Although, from a fiscal point of view, this solution is preferred and politically promoted, it disregards potential hidden costs in form of adverse health effects for the caregiver and possible adjustments of labor supply (e.g. Schmitz and Stroka, 2013; Schmitz and Westphal, 2013; Heger, 2014). Reducing labor supply in turn of starting care provision not only worsens the individual income situation of caregivers but also of social insurers and may even affect productivity and competitiveness of the economy.

Informal caregivers are typically family members, who take on the burden of caring for a loved person. Especially in the light of the demographic change and a resulting shortage of skilled labor, the pressure (or higher opportunity costs) imposed on informal caregivers increases. In this situation many potential caregivers

[1] Note, as the share of persons close to death is obviously higher among the oldest old, health expenditure in an aging society may rise independently of whether age or proximity to death is the major determinant.

Figure 1.2: Care Expenditure, Social Care Insurance in Germany



Own diagram based on data from Bundesministerium für Gesundheit (2014).

decide to take on the double burden of caregiving and full-time-work. An investigation of potential health effects of this double burden can reveal these deteriorating health effects and help to approach the true costs of informal caregiving.
A second factor that is often claimed to be a major driver of health expenditure is technological progress in medicine. Not only is the development and assessment of new medical procedures very costly but also the usage of new technologies certainly does increase the range of diagnostics and enables to treat diseases, which would have been either not diagnosed before or could not be treated (Newhouse, 1992; Okunade and Murthy, 2002; Meropol and Schulman, 2007). As with the demographic change, also technological progress may accommodate some hidden costs which go beyond the direct costs for expensive R&D, assessment procedures and the potentially higher range of diagnosed and treated diseases. New technologies, which are currently in the approval process, or even research activities and rumors may raise hope in patients that their disease might be cured at some point in the future (Philipson et al., 2010). This potentially increases the present demand for medical services and even for risky and marginally effective treatments, as patients hope for a sufficiently long prolongation of life to benefit from a new technology. Such an option value of technological progress may increase health expenditure indirectly via higher demand for medical services.
However, technological progress and demographic change are not the only factors to determine rising health expenditure. Also factors like changes in the awareness for diseases can have a direct impact on health expenditure. These trends in diagnostic strategies are in a sense comparable to technological progress. Just as technological progress allows to diagnose previously undetected diseases and

therefore increases diagnosed number of cases, a change in awareness for diseases may increase the number of diagnoses. In recent years the awareness for mental diseases, be it induced by supply or demand side, drastically increased, directly raising health expenditure (Jacobi, 2009). While the total health expenditure per person has risen by 17% from €2,650 in 2002 to €3,100 in 2008, the figures for mental diseases have increased by 25% from €280 to €350 in the same time period (Gesundheitsberichterstattung des Bundes, 2015). As shown in a very recent publication by a large German insurance company, not only the direct expenditure for treatments are immense but also indirect consequences. The study states that the number of absent days from work due to depression has drastically increased since 2000. They carefully and conservatively estimate the resulting costs of absence to be around 4 billion Euros in 2013. Note, this estimate does not even include productivity loss at work of those who are affected but not absent (Grobe and Steinmann, 2015). The increasing share of expenditure and productivity loss induced by mental diseases calls for investigations of the mechanisms and factors that lead to deteriorating mental health. One such factor that is believed to have an influence on the mental well-being of individuals is their work-environment, as it plays an important role for a person's financial and social stability. There is a large strand of literature claiming that unemployment may have effects on a number of fields of a person's life, such as life satisfaction or long-term labor market outcomes (Clark et al., 2001; Knabe and Rätzel, 2011; Winkelmann and Winkelmann, 1998; Kassenböhmer and Haisken-DeNew, 2009). Although there are some studies analyzing the presence of negative health consequences of unemployment, the results of these studies are ambiguous (e.g. Korpi, 1997; Björklund and Eriksson, 1998; Green, 2011; Browning et al., 2006; Böckerman and Ilmakunnas, 2009; Salm, 2009; Schmitz, 2011). Also the fear of becoming unemployed is believed to negatively affect health. That is potential negative health effects arise even before an actual unemployment spell, which offers a possible explanation for the ambiguous findings on health effects of actual unemployment (Reichert and Tauchmann, 2011). In this connection it is interesting whether these negative effects are found for the persons directly affected only or whether they spill over to persons in the close environment. Such spillover effects would reveal hidden costs of (potential) unemployment or suboptimal employment arrangements that again may increase health expenditure.

A further driving force of health expenditure may be found in inefficiencies on health insurance markets. It is often claimed, that the German health insurance market suffers from an insufficient level of competition. Reform efforts have been made to increase the competition between insurers by trying to encourage the

switching behavior of consumers. Yet, if the insurants are reluctant to switch insurances for whatever reason, enhancing competition is hardly possible. Therefore, evaluating preferences and types of consumers is important to help constructing markets which encourage switching behavior and therefore help to increase efficiency in health insurance markets and reduce expenditures which do not reflect preferences but can be traced back to market inefficiencies.
In this dissertation, I identify and analyze the potential reasons for rising health expenditure explained above, using a wide range of empirical methods.

1.2 The Studies

This cumulative dissertation comprises four distinct studies, each of which sheds light on at least one of the aforementioned factors of rising health expenditure. The first study deals with informal caregiving, an issue that does not only gain importance due to demographic change but that is also connected to mental health. The second study analyzes hidden costs of technological progress which can be found in increased demand for marginally effective treatments. As third study, I introduce a paper that investigates mental spillover effects of the fear of unemployment. An analysis of heterogeneity in preferences and types of consumers of health insurance is undertaken in the fourth study.
While each of these studies analyzes factors that potentially increase health expenditure, they are on distinct topics and make use of different methods. The pool of methods in economics ranges from modern econometric techniques applied on observational data to laboratory experiments, which evolved only recently in economics. Modern econometric techniques are capable of disentangling effects, dealing with endogeneity issues and establish causal links to arrive at reliable estimates. They are, however, often very data demanding and rely on sophisticated methods, which try to replicate ideal experimental conditions to allow causal inferences. On the other hand, experimental economics test hypotheses in a laboratory environment by working with individuals, directly manipulating variables of interest and controlling for factors that influence explaining variables in a controlled environment. Therefore, the experimental approach tries to keep selection issues out of the data right from the start which renders complicated econometric methods obsolete. However, laboratory experiments are often limited to a very small number of observations and the controlled and artificial environments may raise doubts about the external validity of results.
Which approach is to be preferred cannot be resolved in general. Each of the methods has its advantages and disadvantages and relies on a number of assumptions.

A broad discussion of methodology is beyond the scope of this introductory chapter, however as a short note: deciding for one or the other method crucially depends on what question is being analyzed. Therefore, both economic methods should be seen as complements rather than substitutes. To give an example, think of analyzing health effects of unemployment. It is hardly possible (and would be certainly unethical) to manipulate subjects' employment status in the laboratory and observe health outcomes in the long run. However, applying microeconometric techniques to administrative or survey panel data allows disentangling effects to receive reliable estimates of health effects caused by unemployment. Conversely, it is hardly possible to analyze the relative importance of preferences for contract attributes in hypothetical settings using administrative or panel data as it simply does not exist. The questions of how people would behave cannot be answered by analyzing data on revealed preferences but depends on stated preference methods.

Hence, both approaches complement each other to better understand, test and develop economic theory.

In the following, I will give a short summary on each of the four studies, also including the choice of method.

Reconsidering Reconciling: Health Effects of the Double Burden of Caregiving and Full-time Work

Meeting the challenges of longevity is one of the primary political issues of most industrialized countries. Already today there are more than 2.5 million care recipients in Germany, the majority of whom is cared for at home by informal caregivers alone or in cooperation with mobile nursing services (Statistisches Bundesamt, 2013). For full-time working informal care providers this either means reducing labor supply or taking on the double burden of providing care and working full-time. Taking on the double burden may impose considerable strain on caregivers which probably adversely affects their health state.

To identify health effects of the double burden of working full-time and providing informal care, a multinomial endogenous treatment model is applied to representative survey data provided in the German Socio-Economic Panel. The outcome variables are mental and physical component summary scales. The model accounts for endogenous selection into four different states of care and labor provision by estimating treatment and selection effects. Exclusion restrictions are used to identify treatment effects of the four different states. Potential reverse causality issues are minimized by applying a lagged dependent variable approach.

Considerable negative health effects of taking on the double burden are found for

both, mental and physical outcome variables. The negative effects for females are found to be larger than for males.
The double burden seems to induce hidden costs in form of adverse mental health effects for caregivers. Counting against its savings potential and also considering the high expenditure and awareness for mental diseases, it therefore may have the potential to raise health expenditure indirectly.

Risk-Loving in the End? The Role of Option Values in Choosing Risky and Marginally Effective Treatments

A substantial share of health expenditure is induced in the last year of a patient's life. The high demand for marginally effective treatments in terminal care strongly raises health care expenditure and thus is a common target in the health political debate about prioritization in medical care. Literature indicates that technological progress may induce an option value that could lead to risk loving behavior in treatment choice and thus induce high demand for risky terminal care (Philipson et al., 2010). Therefore, the option value, which can be induced by investment in R&D, seeing a new technology entering approval or simply by rumors about future breakthroughs, may not only lead to risk-loving choices but also to increasing health expenditure.
In this paper I analyze the option value as possible reason for stronger preferences for risky and marginally effective end-of-life treatments and risk-loving behavior with respect to remaining life time. I use a discrete choice experiment to evaluate treatment choice behavior in the presence of option values. Subjects are asked to choose between different marginally effective treatments with varying survival distributions. By including an attribute in the questionnaire that describes a new technology, which is potentially being administered to patients at some point in the future, the option value is introduced into the decision scenario.
Results indicate that the option value of a future cure has the potential to lead to higher risk acceptance and preference for risky treatments even for initially risk-averse persons. That is, the option value increases demand for risky and marginally effective treatments and by this raises health expenditure.

Fear of Unemployment and its Effect on the Mental Health of Spouses

As already outlined earlier, there is a rich literature on negative effects of unemployment on various fields of a person's life, while the literature on health effects of unemployment on the unemployed is not so clear. There are studies that do find negative health effects, while other studies do not. However, it has been shown that not only the unemployed themselves are affected by an actual unemployment spell but a negative effect also spills over to their spouses and family members (Winkelmann and Winkelmann, 1995; Siedler, 2011; Kind and Haisken-DeNew, 2012; Marcus, 2013). Reichert and Tauchmann (2011) analyze if even the fear of losing a job affects individuals negatively.

Against this background, chapter 4 analyzes the effect of individual job worries on their spouses' mental health. Therefore, representative survey data from the German Socio-Economic Panel (SOEP) is used to estimate the effect on the mental component summary scale. Possible problems that arise from endogeneity are accounted for by applying panel models. Further exploiting exogenous variation using staff reductions as a proxy for job worries helps to confirm the direction of effects.

The results show that the fear of job loss has considerable negative effects on spouses' mental health, suggesting that adverse health effects may even emerge before an actual unemployment spell. Effects are largest for women whose partner is afraid of losing his job, which may be accredited to classic societal role models in which men are the main income earners. The spillover effect of the fear of unemployment uncovers hidden costs that are connected to (potential) unemployment and suboptimal work conditions. As expenditure for mental diseases accounts for a large and rising share of total health expenditure, detecting such negative mental health consequences is considered important.

How Do Consumers Choose Health Insurance? An Experiment on Heterogeneity in Attribute Tastes and Risk Preferences

Recent health policy reforms try to stimulate switching behavior of consumers in the health insurance market to increase competition among insurance companies. As none of the reforms was particularly successful in setting effective incentives to sustainably stimulate switching it is worthwhile to elicit consumers' preferences. This study uses a laboratory experiment to analyze consumers' tastes in typical contract attributes of health insurances and to investigate their relationship with individual risk preferences. First, subjects make consecutive insurance choices in situations varying in the number and types of contracts offered. Then, individual risk preferences according to cumulative prospect theory are elicited. Applying a latent class model to the choice data reveals five classes of consumers with considerable heterogeneity in tastes for contract attributes. From this, distinct behavioral strategies for each class are inferred.

The majority of subjects use minimax-type strategies focusing on contract attributes rather than evaluating probabilities in order to maximize expected payoffs. Moreover, it is shown that using these strategies helps consumers to choose contracts, which are in line with their individual risk preferences. Results reveal valuable insights for policy makers of how to achieve more efficient consumer choice. Finding a way of accounting for the trade-off between acknowledgment of individual taste heterogeneity and the resulting complexity on health insurance markets is advisable.

2 Reconsidering Reconciling: Health Effects of the Double Burden of Caregiving and Full-time Work

2.1 Introduction

Meeting the challenges of longevity is one of the primary issues of most industrialized countries. The problems arising from the rectangularization of the survival curve are not only of direct financial or fiscal nature as brought about by increasing pension obligations, but also have consequences with respect to securing health services, especially for the elderly. In Germany, for instance, there are more than 2.5 million care recipients already today, the majority of whom is cared for at home by informal caregivers alone or in cooperation with formal ambulatory care by mobile nursing services (Statistisches Bundesamt, 2013). The number of care recipients will increase further in the future and thereby, ceteris paribus, also the demand for informal caregivers.

Informal care provision has two possible consequences for full-time working individuals: (i) they either reduce their labor supply in turn of providing informal care or (ii) they take on the double burden of working full-time and providing care. In the light of demographic aging, reducing labor market participation increases the fiscal challenge of longevity in countries with pay-as-you-go schemes to finance their social insurance system. Moreover, less supply of skilled work can decrease productivity and competitiveness of economies. Therefore, raising labor market participation is a major goal of economic policy[1] and increasing numbers of full-time working individuals who also provide formal care can be seen as killing two birds with one stone: they decrease fiscal expenditures for professional care and simultaneously increase social insurance contributions by their labor market par-

This paper is joint work with Hendrik Schmitz. We thank Dörte Heger and Matthias Westphal for helpful comments. All remaining errors are our own. Financial support by the Fritz Thyssen Stiftung is gratefully acknowledged. Further, we are thankful to the RWI for providing neighborhood-project data.

[1] In Europe, for instance, the European Employment Strategy set up by the European Council in 2000 aims at increasing the labor-force participation, particularly of women.

ticipation. Apart from fiscal issues, informal care is, in general, also preferred by care recipients who may benefit from staying in their familiar environment.
On the other hand, however, care provision is a challenging task and reconciling working and caregiving, that is, taking on a double burden might overstrain caregivers, possibly inducing adverse health effects. Whether or not this is the case is an empirical question and is analyzed in this study.
The literature usually only finds small effects of informal caregiving on labor market outcomes (Bolin et al., 2008; Carmichael and Charles, 1998, 2003; Ciani, 2012; Heitmueller, 2007; Meng, 2013; Nguyen and Connelly, 2014; Lilly et al., 2010; Geyer and Korfhage, 2014). That is, most people tend not to react to a care provision period by adjusting their labor supply. It seems that the consequences of resigning or reducing hours are too severe to justify this step for most individuals especially facing the uncertainty about the duration of the double burden status.
Although the economic literature on health effects of informal caregiving is less comprehensive, there have recently been some studies published in this field. Bobinac et al. (2010) find detrimental effects of informal care provision on individual well-being. In line with that, Coe and Van Houtven (2009) find negative effects on mental health, especially of female care providers, while they do not find negative effects on single physical indications, such as blood pressure. Using SHARE data on European women aged 50-70, Heger (2014) finds negative mental health effects of providing care to parents, while the results for physical health measures are mixed. Schmitz and Westphal (2013) find a detrimental short-term effect of caregiving for females, which, however, fades out over a five year time period. Finally, Do et al. (2015) report negative effects on health of providing informal care for South Korean females who care for their parents-in-law.
This study focusses on the double burden of working full-time and providing care at the same time and to the best of our knowledge, there is only one existing study that explicitly looks at its health effects. Schmitz and Stroka (2013) use a data set from the largest German health insurance company to analyze the effect of the double burden on drug prescriptions for mental and physical diseases. They find an increased use of antidepressants with female caregivers who take on the double burden, indicating a worse mental health status but do not find significant results for drug intake for physical diseases.
We use data from the German Socio-Economic Panel (SOEP) of the years 2002 – 2010 and composite measures of physical and mental health from the SOEP version of the SF12v2-questionnaire. In estimating health effects of care provision there is an endogeneity problem of care. The decision to provide care is most likely correlated with other unobserved time varying and time invariant factors that also

affect health. Examples could be the general frailty or a health shock of the caregiver. We apply the multinomial treatment model developed by Deb and Trivedi (2006a) and exclusion restrictions to account for this endogeneity problem. Thus, our approach differs from the one applied by Schmitz and Stroka (2013) whose administrative dataset does not include many socio-economic variables which potentially would serve as instruments. Thus, their analysis relies on fixed effects methods that only account for time-invariant unobserved heterogeneity.

Our results suggest, that taking on the double burden impairs individual's physical and mental health state. This result holds for the pooled sample as well as subsamples of men and women (except for physical effects for males). Additionally, also caring only while not being employed full-time seems to worsen the mental health state of females. The results are found to be robust against changes in the definition of caregiving, dependent variables and exclusion restrictions. We find the detrimental effects of the double burden to be in line with Schmitz and Stroka (2013).

The paper is organized as follows. Section 2.2 starts out by describing the empirical strategy. Section 2.3 describes the dataset and important variables used in the estimation stage. The results are reported in Section 2.4. In Section 2.5 we evaluate the robustness of results against changes in definitions and specifications before Section 2.6 concludes.

2.2 Empirical Strategy

We assign individuals into four mutually exclusive states, depending on their choices to work in the labor market and to provide care as shown in Figure 2.1. We call this the Caregiving and Labor Status (CLS), for simplicity.

Figure 2.1: Caregiving and Labor Status

		Care Provision	
		No	Yes
Full-time Work	No	No Work, No Care	Care Only
	Yes	Work Only	Double Burden

Transforming this multinomial variable into mutually exclusive dummy variables, a benchmark linear estimation model to analyze the research question reads

$$Health_{it} = \beta_0 + \beta_1 CareOnly_{it} + \beta_2 WorkOnly_{it} + \beta_3 DoubleBurden_{it} + x_{it}'\gamma + \varepsilon_{it} \tag{2.1}$$

where $Health_{it}$ is a health measure (to be specified in Section 2.3) of individual i in wave t, $CareOnly_{it}$ equals 1 if the CLS is care but no full-time work, $WorkOnly_{it}$ indicates working full-time only and $DoubleBurden_{it}$ working full-time and additionally providing care. No full-time work and no care provision serves as reference category. As the potential health effects of *DoubleBurden* are supposed to run via stress imposed on the carer we explicitly focus on full-time workers. That is, *NoWorkNoCare* and *CareOnly* also include part-time employed persons. Further socio-economic characteristics are included in the vector x_{it}.

This model can be estimated by OLS. However, most likely the assignment of individuals into one or the other CLS is endogenous, rendering estimated coefficients from OLS inconsistent. To account for this, we apply a multinomial treatment model suggested by Deb and Trivedi (2006a,b). In this model we can jointly estimate the parameters determining the CLS and those of the outcome equation where both equations are linked by common latent factors.

For the "treatment" (that is, the CLS), the following multinomial logit model is specified

$$Pr(CLS_{ij}|z_i, l_i) = \frac{exp(z_i'\alpha_j + \delta_j l_i^j)}{1 + \sum_{k=1}^{J} exp(z_i'\alpha_k + \delta_k l_i^k)} \tag{2.2}$$

where CLS_{ij} is the CLS $j \in \{1, 2, 3, 4\}$ of individual i.[2] From Equation (2.2), the probability of belonging to a certain CLS is determined by observable variables included in z_i and unobserved individual characteristics, that affect outcome and treatment choice, as captured by the latent factors l_i^j.

The outcome equation (2.3) specifies the expected value of the health status as linear function of a set of socio-economic controls in x_i, binary indicators for the CLS and the latent factors (l_i^j).

$$\begin{aligned} Health_i(CLS_i, x_i, l_i) &= \beta_0 + \beta_1 CareOnly_i + \beta_2 WorkOnly_i + \beta_3 DoubleBurden_i \\ &+ \lambda_1 l_i^{CareOnly} + \lambda_2 l_i^{WorkOnly} + \lambda_3 l_i^{DoubleBurden} + x_i'\gamma + \varepsilon_i \end{aligned} \tag{2.3}$$

[2] We drop the time indicator t for simplicity in the following.

The latent factors are assumed to follow a standard normal distribution and capture unobserved heterogeneity. That is, based on unobserved characteristics and relative to the respective base status, a positive and significant factor loading λ for some status suggests positive selection of healthier individuals into this CLS. As such, the λs are interpreted as selection terms. Identification is via exclusion restrictions as the vector z_i in Equation 2.2 includes all variables in x_i and some more (the instruments).
We apply the Stata routine `mtreatreg` (Deb and Trivedi, 2006a), which conducts a maximum simulated likelihood estimation of the joint model based on Halton sequences.[3] See (Deb and Trivedi, 2006b) for a more formal derivation and the general form of the log-likelihood function that is maximized.

Control variables and instruments

The vector of observable variables x_i includes standard controls such as age, educational level, marital status, a binary indicator of children in the household, nationality, living in a rural area, and dummies for the 16 federal states. In order to reduce concerns of selection of healthy individuals into care, full-time work and, especially, the combination of both, it also includes the lagged health status.
Exogenous variation is exploited to improve identification by using variables in z_i that influence the choice of treatment but apart from that do not have direct health effects or correlations with unobserved factors. The set of variables assumed to fulfill the exclusion restriction contains

- dismissal due to plant closure in the two previous years
- the number of siblings
- regional unemployment rates
- regional number of nursing home places per person
- the personnel employed in the professional care sector in a region per person

Plant closure has been argued to offer exogenous variation in labor force participation and, consequently, has been widely used in related fields of research (Schmitz, 2011; Salm, 2009; Browning et al., 2006). Thus, we assume plant closures to be exogenous events with no direct influence on health (that goes beyond the

[3]Deb and Trivedi (2006a) suggest choosing the number of Halton draws to be at least as large as the square root of observations to eliminate simulation bias. Hence, we use 400 draws which is ample for roughly 36,000 observations in the pooled sample.

one through the CLS). However, being dismissed from your job might well affect the probability of being assigned to a specific CLS. For example, belonging to work only is directly negatively affected by exogenous entry into unemployment caused by a close-down of the employer.

The number of siblings that are alive is believed to influence the probability to care for elderly individuals, as a sibling might take over the burden of caring for their parents. Apart from underlying genetic factors, which cannot be completely ruled out, we believe this variable also fulfills the requirements to offer exogenous variation.[4] The remaining three instruments (regional unemployment rates, number of nursing home places per person and the personnel employed in the professional care sector per person) all offer the benefit of regional variation on county level.

As there might be consequences of regional unemployment rates with respect to health which run over channels apart from own unemployment, this aspect needs consideration. There is a rich literature on neighborhood effects on health (see Diez Roux and Mair, 2010 for an overview). Typical factors that are argued to influence health are infrastructure, surrounding, social composition or the density of population. We approach this issue by including federal state dummies to control for regional differences. Further we use a binary indicator of rural areas to account for potential structural differences arising from population-based characteristics and in turn also controlling for surrounding and infrastructural aspects. Therefore the exclusion restriction is believed to hold as the potential channels over which health might be influenced should be captured by the regional dummies.

The number of employees in the long-term care sector and the number of nursing home places reflect the supply of formal care in the county. This might affect the likelihood to provide care as there is a well established substitution between formal and informal care (Bonsang, 2009). On the other hand we do not believe these variables to have an own effect on the caregiver's health. At best one might be afraid that these variables capture other regional characteristics such as the income level. Again, however, this should be captured by federal state dummies.

2.3 Data

We use representative panel data provided in the German Socio-Economic Panel (SOEP). The longitudinal German survey entails comprehensive individual- and household-level data on an annual basis. In particular, data for a large set of so-

[4]We find our results to be robust against not employing this instrument. However, as siblings contribute to explain treatment choice for subsamples, we stick to this approach as preferred specification. For details see Section 2.5.

cioeconomic characteristics, such as working, financial or health conditions can be found for all members of a representative set of households aged at least 17. The first wave of the SOEP was conducted in 1984 and subsequently refreshed and enlarged several times. In 2013 (SOEPv29), the panel comprises information on more than 20,000 individuals (DIW, 2014). The data are merged with regional unemployment rates at zip-code level and nursing home places at the county level.

Care and labor force status

We restrict the sample to working age individuals between 25 and 64 years, as 65 is the statutory retirement age in Germany. The definition of care provision and labor market status is based on time-use questions provided in the SOEP. Respondents are asked the following question: "What is a typical weekday like for you? How many hours per normal workday do you spend on the following activities?". Among the eight possible answers are: "Care and support of persons in need of care" as well as "Work/apprenticeship". All persons that state to spend at least one hour a day on providing care to people in need of care are defined as informal caregivers.[5] Unfortunately, the panel does neither provide us with the relationship between caregiver and care recipient, nor with the intensity of caring efforts in terms of the level of caring needs of the recipient. Hence, we can only approximate intensity by the number of hours devoted to caregiving per day. With respect to working status, individuals are defined as full-time workers if their time-use for paid work exceeds seven hours a day. That is, a minimum working time per week of 35 hours, which is the currently observed lower bound for full-time-work in Germany.[6]

Table 2.1 provides an overview over the four CLS. The largest category is *WorkOnly* which comprises 55.69% of all observations, while 38.15% neither work nor provide care. The group of those who provide care only make 3.73% of the sample. The remaining 2.43% take on the double burden. There is a large difference in CLS-composition with respect to gender. Females tend to work less on full-time contracts while providing more informal care. When it comes to taking on the double burden, there is no large discrepancy found between sexes.

[5]This question does not refer to child care which is a separate category in the time use questionnaire. The results are robust to choosing two hours of care to define care provision instead of one (see Section 2.5).

[6]The mean of weekly hours for full-time-workers in Germany is around 42h/week in 2012. In some large industries like metal and electronics, employess work for 35h/week. See www.destatis.de for details. Again, results are robust to choosing six or eight hours of work to define full-time work (see Section 2.5).

Table 2.1: Sizes of Caregiving and Labor Statuses

	Pooled		Female		Male	
No work, No Care	13,728	(38.15%)	10,246	(54.25%)	3,482	(20.37%)
Care Only	1,342	(3.73%)	1,079	(5.71%)	263	(1.54%)
Work Only	20,039	(55.69%)	7,087	(37.53%)	12,952	(75.76%)
Double Burden	873	(2.43%)	473	(2.50%)	400	(2.34%)
Total	35,982	(100.00%)	18,885	(100.00%)	17,097	(100.00%)

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. Absolute and relative sizes of CLS based on caring at least 1h/day and working at least 7h/day.

Table 2.2 inspects the dynamics of the CLS. We show year-to-year-transitions between the CLS.[7] The first column shows that among all who take on the double burden in year $t+1$, 550 had already shouldered it in year t. Among those who newly reconcile working and caring, 81% (=509/(509+70+50)) had worked full-time only before. Only small numbers start their double burden by adding full-time work to an ongoing caregiving episode (6%) or even start both working and caregiving at the same time (4%). This fits to the notion of most of the previous literature: upon caregiving episodes the vast majority keeps their job while also providing care. Thus, our main interest shall lie in the different effects of *WorkOnly* and *DoubleBurden*.

Table 2.2: Dynamics of Caregiving and Labor Statuses

$t \downarrow$	$t+1 \rightarrow$ Double burden	Only Work	Only Care	No Work, No Care	Total
Double burden	550	440	88	63	1,141
Only Work	509	25,627	93	2,524	28,753
Only Care	70	71	1,081	559	1,781
No Work, No Care	50	2,331	588	15,991	18,960
Total	1,179	28,469	1,850	19,137	50,635

Note: Authors' calculations based on the SOEP for the years 2001–2011.

[7] Note that this is a different sample than the one for the main analysis. To increase the numbers of observations we do not only stick to every second wave where the outcome measures are available. Transitions between two years show similar patterns, however.

Health status

To get a complete picture of individuals' health, we use two health measures provided in the SOEP. The first one is the mental component summary scale (MCS), which measures the current mental health status of a respondent. The second measure is the physical component summary scale (PCS), which is the physical equivalent of the MCS. Both variables are created by explorative factor analysis of six questions each. The questions are based on the SOEP version of the SF12v2-questionnaire, which is biennially included in SOEP since 2002.[8] The score ranges from 0 to 100, with a mean at 50 and a standard deviation of 10 for the survey year 2004 (Andersen et al., 2007). For both, MCS and PCS, a higher value indicates better health. Component summary scales are widely used in health economics applications (Schmitz, 2011; Marcus, 2013; Schmitz and Westphal, 2013). Recent research provide some evidence for MCS being a good measure of individual mental health conditions (Gill et al., 2007; Salyers et al., 2000).

Due to the biennial character of the dependent variables and the inclusion of lagged variables we use outcome variables from the waves 2004, 2006, 2008 and 2010. After dropping observations with missing values (in particular in the regional variables due to restricted availability of the regional indicator in the SOEP we use 35,982 person-year observations stemming from 10,100 individuals in the final estimation sample.

Table 2.3 reports means in outcomes by the four CLS groups. We see that individuals who work full-time only have the best health status, while those who care only have the worst in the full sample. No work and no care as well as individuals taking on the double burden are in between. These results change if we restrict the sample to men or women. It is hard, however, to interpret these unconditional means as they probably capture many different effects (effects of CLS on health and vice versa, correlations with observed and unobserved effects). It is the goal of the regression analysis to disentangle these effects.

The control variables and instruments used in the regression were mentioned in Section 2.2 already. Table A2.2 in the Appendix reports descriptive statistics of these variables.

[8] The SF-12v2 questionnaire is shown in Table A2.1 the Appendix.

Table 2.3: Descriptive Statistics

	MCS	PCS
Pooled sample		
Care Only	47.78	47.12
Work Only	50.50	52.48
Double Burden	48.07	49.63
No Work, No Care	49.41	49.34
Females		
Care Only	47.39	47.81
Work Only	49.16	52.15
Double Burden	47.05	49.55
No Work, No Care	49.29	50.12
Males		
Care Only	49.38	44.27
Work Only	51.24	52.66
Double Burden	49.27	49.73
No Work, No Care	49.76	47.07

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. Unconditional means for dependent variables by subgroups.

2.4 Results

2.4.1 OLS as a Benchmark

As a benchmark, we estimate a simple OLS model of Equation (1) assuming exogeneity of labor supply and care provision and report the results in Table 2.4. We see that *DoubleBurden* and *CareOnly* both have a significantly negative coefficient of similar size for the pooled sample. That is, both are found to be correlated with a lower mental health status of care providers. This is also found for the subsample of females whereas the relationship is negative but insignificant for males. Working only has a significantly positive coefficient in the pooled sample and for males. All in all, the coefficients are as expected. Those for care provision might be underestimated if there is a selection of more healthy individuals into care provision which is not accounted for by OLS.

The results for PCS are slightly different. While we find negative point estimates for caring only throughout all subsamples and positive ones for work only (both as in the case of MCS), there are positive point estimates for the double burden. Again, these results should not be interpreted as causal, however, and might be induced by selection into and out of care provision not accounted for by OLS. We therefore address the endogeneity by applying the multinomial treatment model.

Table 2.4: OLS

	Pooled	Female	Male
Dependent Variable: MCS			
Care Only	-1.264^{***}	-1.605^{***}	-0.159
	(0.261)	(0.286)	(0.641)
Work Only	0.397^{***}	0.157	1.061^{***}
	(0.111)	(0.149)	(0.185)
Double Burden	-1.182^{***}	-1.466^{***}	-0.459
	(0.298)	(0.416)	(0.436)
MCS_{t-1}	0.494^{***}	0.487^{***}	0.499^{***}
	(0.006)	(0.008)	(0.009)
Constant	73.390^{***}	70.300^{***}	76.169^{***}
	(0.646)	(0.914)	(0.851)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
Dependent Variable: PCS			
Care Only	-0.319	-0.371	-0.375
	(0.215)	(0.244)	(0.460)
Work Only	0.903^{***}	0.486^{***}	1.789^{***}
	(0.088)	(0.115)	(0.156)
Double Burden	0.508	0.123	1.439^{***}
	(0.247)	(0.352)	(0.350)
PCS_{t-1}	0.582^{***}	0.576^{***}	0.579^{***}
	(0.006)	(0.008)	(0.009)
Constant	79.370^{***}	77.713^{***}	80.484^{***}
	(0.512)	(0.692)	(0.749)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
N	35,982	18,885	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses.

2.4.2 Multinomial treatment model

Choice Equation

We start by briefly discussing the results of the choice equation. These results do not differ much between both outcome variables. Moreover, as we prefer to report marginal effects instead of coefficients, we show, for simplicity, marginal effects of the separately estimated choice equation without latent factors. The results are reported in Table 2.5. Coefficients are reported in A2.3 in the Appendix. By comparing them with the coefficients of the choice equation in the jointly estimated model (Table A2.4), we see that the differences are negligibly small.

Table 2.5: Marginal Effects of Choice Equation (pooled sample)

	Pr(NoWorkNoCare)	Pr(CareOnly)	Pr(WorkOnly)	Pr(DoubleBurden)
Instruments				
Plant Closure	0.300***	0.019***	−0.307***	−0.012***
	(0.022)	(0.007)	(0.022)	(0.003)
Number of Siblings	0.002	−0.000	−0.001	−0.001
	(0.002)	(0.001)	(0.003)	(0.001)
Unempl. rate (Female)	0.006***	0.001**	−0.008***	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Unempl. rate (Male)	−0.001	−0.001**	0.002	−0.001
	(0.002)	(0.000)	(0.002)	(0.000)
Nursing Care Places	0.003	−0.002**	0.000	−0.001
	(0.003)	(0.001)	(0.003)	(0.001)
Employees in Care	0.002	0.002**	−0.007*	0.003***
	(0.004)	(0.001)	(0.004)	(0.001)
Other controls				
Age: 35-44	−0.075***	0.007	0.045***	0.023***
	(0.010)	(0.004)	(0.011)	(0.006)
Age: 45-54	−0.039***	0.036***	−0.040***	0.043***
	(0.012)	(0.006)	(0.013)	(0.007)
Age: 55-64	0.238***	0.082***	−0.347***	0.027***
	(0.014)	(0.010)	(0.013)	(0.007)
Marital Status	0.037***	0.012***	−0.054***	0.006***
	(0.010)	(0.002)	(0.010)	(0.002)
Children in HH	0.183***	0.003	−0.174***	−0.012***
	(0.010)	(0.002)	(0.010)	(0.002)
Education: General	−0.074**	−0.005	0.086**	−0.007
	(0.035)	(0.007)	(0.038)	(0.007)
Education:Middle	−0.144***	−0.007	0.158***	−0.007
	(0.036)	(0.007)	(0.038)	(0.009)
Education:voc. train.	−0.216***	−0.006	0.223***	−0.001
	(0.026)	(0.007)	(0.030)	(0.009)
Education: University	−0.291***	−0.019***	0.312***	−0.002
	(0.027)	(0.005)	(0.029)	(0.008)
Education:High Sch.	−0.180***	−0.013**	0.194***	−0.001
	(0.029)	(0.005)	(0.032)	(0.009)
Foreign	0.051***	−0.010***	−0.028*	−0.012***
	(0.017)	(0.003)	(0.017)	(0.003)
Rural Area	0.002	0.004	−0.009	0.003
	(0.012)	(0.003)	(0.012)	(0.003)
2006	−0.028***	−0.003	0.032***	−0.000
	(0.008)	(0.002)	(0.008)	(0.002)
2008	−0.027***	−0.003	0.029***	0.001
	(0.010)	(0.002)	(0.010)	(0.003)
2010	−0.024**	−0.004*	0.030***	−0.002
	(0.010)	(0.002)	(0.010)	(0.002)
Female	0.373***	0.038***	−0.413***	0.002
	(0.007)	(0.002)	(0.007)	(0.002)

Note: These are marginal effects after a single equation multinomial logit estimation of CLS on controls. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Standard errors in parentheses. N=35,982. Federal state dummies not shown. Coefficients of the estimation reported in Table A2.3 in the Appendix.

The results suggest that middle-agers have an increased probability to give care and also to shoulder the double burden, which is in line with expectations, considering the age of parents in need of care. With respect to gender, we find women to be more likely to belong to the care-only group while they are less likely working full-time. This does not come as a surprise as most informal care in Germany is provided by women in the age of 35 to 65 and, moreover, women are more likely to work part-time than men. More education goes along with increased probability of working only and decreased probability of not working and not providing care. Those with highest education levels are less likely to provide care.

The instruments show the expected direction of marginal effects, that is, being laid off due to plant closure in the previous two years significantly decreases the probability to work and therefore also to take on the double burden. Higher regional unemployment rates for females have a negative coefficient for the work-only class, while male unemployment rates lead to a lower probability of providing care only. This might be accredited to a strained situation on the labor market and presumably traditional gender roles with regard to house- and paid work in many families. The number of regional nursing care places per person reasonably decreases the probability of giving care only. However, the personnel employed in the professional care sector per person in a region has a significantly positive coefficient for care only as well as the double burden and decreases the probability to work only. This might seem contradicting at first glance but seems reasonable if we consider what is actually captured here. The personnel employed in care includes mobile nursing services, utilization of which usually does not render further informal care obsolete as stationary care does. According to official German data, more than 20% of all care recipients are cared for at home with some help from mobile nursing services (Statistisches Bundesamt, 2013). Overall, we find the marginal effects of the exclusion restrictions to point in a reasonable direction and explain the endogenous decisions to work and provide care to a considerable amount. Only the number of siblings does not seem to play a role statistically.

Outcome Equation

The multinomial treatment choice model accounts for endogenous selection and estimates treatment effects on health status. The treatment effects can directly be interpreted as in a standard linear model relative to the reference category $NoWork, NoCare$. Table 2.6 shows the results for mental health.[9] For the pooled sample, we find a significant effect of the double burden. That is, an individual (as good as) randomly assigned to the double burden would experience a decrease in MCS by 4.946 points compared to a person assigned to the reference category. This

[9] Here, we focus on the most relevant coefficients. Full estimation results are reported in Tables A2.4 – A2.9 in the Appendix.

effect is of considerable size as it accounts for roughly 50% of a standard deviation of MCS. As we suspect differences in sensitivity between genders, we re-estimate the model for female and male subsamples. Columns 2 and 3 of Table 2.6 present the results for the sex-split samples. We find a large detrimental effect of the double burden for both sexes (-5.777 or 58% of a SD for females and -3.897 or 39% of a SD for males). As pointed out by the descriptive dynamics in Section 2.3 the most

Table 2.6: MCS – Treatment and Selection Effects

	Pooled	Female	Male
Care Only	-0.744	-3.243^{***}	1.543^{*}
	(0.653)	(0.985)	(0.902)
Work Only	1.101^{***}	1.113^{***}	1.884^{***}
	(0.403)	(0.432)	(0.560)
Double Burden	-4.946^{***}	-5.777^{***}	-3.897^{***}
	(0.501)	(0.668)	(0.655)
No Work, No Care	*Reference Category*		
MCS_{t-1}	0.494^{***}	0.486^{***}	0.499^{***}
	(0.006)	(0.008)	(0.009)
Constant	22.989^{***}	21.705^{***}	23.501^{***}
	(0.604)	(0.735)	(0.835)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
lnalpha	1.988^{***}	1.945^{***}	1.932^{***}
	(0.033)	(0.043)	(0.044)
$\lambda_{CareOnly}$	-0.552	1.812^{*}	-1.786^{***}
	(0.656)	(1.042)	(0.664)
$\lambda_{WorkOnly}$	-0.881^{*}	-1.202^{***}	-1.018
	(0.468)	(0.475)	(0.640)
$\lambda_{DoubleBurden}$	4.020^{***}	4.658^{***}	3.663^{***}
	(0.438)	(0.566)	(0.524)
N	35,982	18,885	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses. Full estimation results reported in Tables A2.4 - A2.6 in the Appendix.

relevant comparison may be between those who work only and those who take on the double burden as most observations that enter the double burden worked only in the previous period. For the pooled sample we find that taking on the double burden compared to working only has an effect of around -6.0 points (-4.946 - 1.101) on the MCS-scale. For females the respective effect on MCS is -6.89 while it is again smaller for males with -5.78.

For the physical health effects of double burden (Table 2.7), the results are similar to the MCS results but smaller in magnitude. We find a detrimental effect in the pooled sample of -2.143 which, however, accounts for roughly 21% of a standard deviation of PCS. The double burden is also found to decrease the physical health of women significantly. The effect is again smaller than for MCS (-2.327) but of relevant size – especially considering that the effect is believed to mainly work over the channel of stress imposed on the carer, which only indirectly affects physical health outcomes. While the point estimate for the male subsample loses significance, the sign remains unchanged.
We find the effect of taking on the double burden compared to working only accounting to -3.7 PCS-points for the pooled sample and -4.135 for females. As mentioned before we do not find a statistically significant effect for the double burden for males.

Table 2.7: PCS – Treatment and Selection Effects

	Pooled	Female	Male
Care Only	0.258	−0.063	−0.650
	(0.361)	(0.600)	(1.021)
Work Only	1.552***	1.808***	2.581***
	(0.413)	(0.490)	(0.586)
Double Burden	−2.143***	−2.327***	−1.016
	(0.475)	(0.673)	(0.772)
No Work, No Care	*Reference Category*		
PCS_{t-1}	0.581***	0.576***	0.579***
	(0.006)	(0.008)	(0.009)
Constant	20.783***	20.229***	21.530***
	(0.539)	(0.620)	(0.774)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
lnalpha	1.809***	1.832***	1.786***
	(0.039)	(0.049)	(0.067)
$\lambda_{CareOnly}$	−0.611**	−0.452	0.294
	(0.310)	(0.609)	(0.963)
$\lambda_{WorkOnly}$	−0.801*	−1.592***	−0.990
	(0.485)	(0.558)	(0.696)
$\lambda_{DoubleBurden}$	2.838***	2.659***	2.631***
	(0.443)	(0.620)	(0.765)
N	35,982	18,885	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses. Full estimation results reported in Tables A2.7 - A2.9 in the Appendix.

The coefficients estimated from the multinomial treatment choice model point towards a larger detrimental effect of taking on the double burden on health than OLS as it accounts for endogenous selection. The $\lambda_{DoubleBurden}$ shows the selection into double burden on unobservables that affect the outcome variable. The parameter of 4.020 in the MCS equation (2.838 in PCS) shows that an individual that is more likely to choose to care and work simultaneously has a higher MCS (PCS) compared to a person that is more likely to belong to the reference group. That is, we find significant and large positive selection of healthy individuals into the double burden of working full-time and providing informal care. This selection effect is found to be of similar size across all subsamples.

We now briefly turn to the other CLSs in Tables 2.6 and 2.7. For *CareOnly*, we do not find significant effects in the pooled samples for neither of the two health measures. However, there exists a considerable negative effect of providing care compared to neither full-time work nor care provision on MCS (-3.243) for females, which is close in magnitude to what Schmitz and Westphal (2013) find as short-term effects. Finally, there seems to be a positive effect of working full-time only throughout all subsamples on both, MCS and PCS.

The negative effects of both, *DoubleBurden* and *CareOnly*, on health are larger for females than for males. Although health effects are supposed to mainly work through the channel of strain imposed on the carer, there is room for parallel channels. The difference in effects might be explained by gender role models. One might suspect a detrimental effect of sympathizing with the care recipient to work along with the imposed stress (the "family effect"). This becomes especially apparent if we compare the effects across specifications. We find the harming effect of double burden to be larger for women. Further, we cannot identify a physical effect for care only across all subsamples, while the effects for MCS is negative and large for women and positive for men. This strong effect with respect to mental health for women does not spill over to worsen physical conditions. Men could benefit from being useful in terms of mental health while for women, the sympathizing or family effect largely prevails. As the family effect presumably plays a less important role in PCS, this gives a hint that a family effect might play a role in gender differences. Unfortunately, the data does not allow for disentangling family effects from stress effects – see Bobinac et al. (2010) for a closer consideration of these effects.

2.5 Robustness Checks

We aim at enhancing credibility of our findings by running several robustness checks. The results are reported in Table 2.8 for changes on the right hand side of the model and Table 2.9 for changes on the left hand side.

2.5.1 Changes in the Explanatory Variables

The number of siblings – although frequently used in the previous literature as instruments – might comprise some underlying genetic and family factors which may threaten its validity as an instrument. Moreover, we do not find large explanatory power of the exclusion restriction for treatment choice in the pooled as well as in the female sample. We therefore re-estimate the model without the number of siblings in the list of instrumental variables. The results are reported in Table 2.8, column (2).[10] The coefficients only change marginally. We therefore conclude that our results are robust against using the number of siblings as an instrument. We, nevertheless, prefer inclusion of the variable in our main specification as it significantly contributes to explaining treatment choice for the male subsample (results not reported but available upon request).

As the SOEP does not provide us with direct measures of care intensity, we approximate intensity by increasing the time threshold in the definition of caregivers. We now consider individuals as informal caregivers if their time use for providing care is at least two hours a day. This obviously decreases the number of observations for those CLSs that count caregivers, i.e. care only and double burden, while it enlarges the two remaining CLSs. The group of those that take on the double burden shrinks from 873 to only 277 when applying the new threshold. Unfortunately, this change in treatment group sizes comes at the cost of not being able to estimate effects for the sex-split samples, as the maximum simulated likelihood estimation of our model does not achieve convergence within a reasonable number of iterations. Results are shown in Table 2.8, column (3). The effects for MCS support our result from the preferred specifications. We find similar effects for taking on the double burden. For PCS, the the coefficient of *DoubleBurden* is estimated less precisely but points into the same direction. As such, the results can be seen as indicator of robustness against changes in definition of informal caregiver status. Increasing the threshold for being a caregiver further is not reasonable as the treatment group sizes become too small for the CLSs, which include caregivers.

While the preferred specification uses the threshold of 7h/day as it is a reasonable fit to German legislation we also use 6h and 8h a day to check the robustness

[10]Column (1) repeats the results from the baseline specification.

Table 2.8: Robustness Checks

		Main Specification (1)	No siblings as exclusion restrictions (2)	Care Provision at least 2h per day (3)	Full-time Work 6h/day (4)	Full-time Work 8h/day (5)	No Lagged Dependent Variable (6)
MCS	Care Only	-0.744	-0.734	-1.779**	-0.751	-0.711	-0.907
		(0.653)	(0.657)	(0.742)	(0.782)	(0.633)	(0.705)
	Work Only	1.101***	1.111***	0.542	1.199***	1.206***	2.535***
		(0.403)	(0.402)	(0.385)	(0.408)	(0.419)	(0.534)
	Double Burden	-4.946***	-4.943***	-4.569***	-4.855***	-5.233***	-7.418***
		(0.501)	(0.502)	(0.839)	(0.511)	(0.476)	(0.513)
PCS	Care Only	0.258	0.242	-0.013	0.138	0.332	-0.104
		(0.361)	(0.362)	(0.403)	(0.385)	(0.340)	(0.482)
	Work Only	1.552***	1.527***	0.902***	1.311***	1.576***	3.122***
		(0.413)	(0.415)	(0.322)	(0.391)	(0.405)	(0.616)
	Double Burden	-2.143***	-2.125***	-1.294	-2.001***	-2.297***	-3.691***
		(0.475)	(0.482)	(0.889)	(0.548)	(0.457)	(0.556)

Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** $p<0.01$;** $p<0.05$;* $p<0.1$. Standard errors (clustered on individual level) in parentheses. Full estimation results reported in Table A2.10 - A2.15 in the Appendix.

of our results, shown in columns (4) and (5). Based on the suspicion, that strain drives the results, the coefficients show the expected direction of effects. That is, for 6 hours of daily work the deteriorating effect of the double burden is slightly smaller, while the corresponding effect is larger in case of 8 hours of daily time devoted to paid work.

Finally, column (6) presents results of a specification omitting the lagged dependent variable. In this case, the coefficients of the double burden strongly increase in magnitude.

2.5.2 Changing the Dependent Variable

Table 2.9: Robustness Check – Health-Satisfaction

	Pooled	Female	Male
Care Only	0.170**	−0.102	0.012
	(0.082)	(0.132)	(0.134)
Work Only	0.410***	0.303***	0.575***
	(0.062)	(0.093)	(0.087)
Double Burden	−0.697***	−0.913***	−0.428***
	(0.069)	(0.095)	(0.124)
No Work, No Care	*Reference Category*		
Health Satisfaction$_{t-1}$	0.591***	0.579***	0.600***
	(0.005)	(0.006)	(0.007)
Constant	8.197***	8.132***	8.351***
	(0.079)	(0.102)	(0.104)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
lnalpha	0.327***	0.304***	0.351***
	(0.025)	(0.035)	(0.042)
$\lambda_{CareOnly}$	−0.255***	0.007	−0.043
	(0.079)	(0.136)	(0.105)
$\lambda_{WorkOnly}$	−0.300***	−0.248**	−0.341***
	(0.072)	(0.107)	(0.101)
$\lambda_{DoubleBurden}$	0.775***	0.935***	0.655***
	(0.056)	(0.076)	(0.112)
N	70,043	36,818	33,225

Note: Authors' calculations based on the SOEP for the years 2004 - 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses.

MCS and PCS measure different dimensions of individual health and as such are not closely interrelated (Correlation: -0.004). There is another variable provided in SOEP which collapses both dimensions into one variable: health satisfaction. In our case, it has the advantage of being included in SOEP annually, which allows us to nearly double the sample size. This in turn comes at the cost of being a more subjective variable compared to the component summary scales (which are sometimes labeled "quasi-objective") and of being categorical. The focus of this variable is to gather information about the individual satisfaction with health. Respondents are directly asked "How satisfied are you with your health?". Answers are on an 11-point scale, ranging from *0 – completely dissatisfied* to *10 – completely satisfied*. Health satisfaction is found to be correlated with both, MCS (Correlation: 0.328) and PCS (Correlation: 0.624) in our data. The mean of health satisfaction in our sample is 6.731 with a standard deviation of 2.097. We use this variable to support our findings concerning both outcomes. The results show significant negative effects for the double burden of relevant size for both, men and women (33.2% of a standard deviation for the pooled sample, 20.4% for men 43.5% for women). Although health satisfaction probably does not capture the same underlying health state as the component summary scales, results support the detrimental health effect of the double burden found from our preferred outcome measure.

2.6 Conclusion

In this study we analyze health effects of the double burden of informal care provision and full-time employment. We apply a multinomial endogenous treatment model developed by Deb and Trivedi (2006b) with four possible treatments, i.e. different combinations of caregiving and labor supply. The empirical model jointly estimates treatment and selection effects and by this corrects for selection into one or the other caregiving and labor status. Using German Socio-Economic Panel data allows us to measure comprehensive mental and physical health states along with further characteristics of caregivers.

Our results suggest that taking on the double burden significantly decreases physical and mental health. We find worsening effects across all specifications with the exception of physical effects for men. Furthermore, there is evidence that females react more strongly to informal care provision than men do. That is, not only is the effect of the double burden considerably larger but also caregiving alone seems to affect the mental health state of women negatively.

Some reforms are already under way, such as a the "income replacement benefit for a ten-day absence" from work, which is planned to be introduced in Germany in 2015.[11] This measure, however, focuses on mitigation of short term effects to help to adapt to the new situation of long-term care provision after e.g. a stroke of a parent. Beyond that, plans also intend to increase expenditures in mobile nursing services, which might help organising informal care at home. Even though this seems to point into the right direction to improve the situation of informal caregivers, evaluation of reforms and their effects remains necessary in the future. Higher expenditures for mobile nursing services, for example, might well lead to more people taking on the double burden and hence more persons being adversely affected. Unfortunately, we cannot distinguish between informal caregivers, who provide care solely on their own and those who are supported by mobile nursing services in this study. There might be differences in that mobile nursing services may take over the most intense tasks, which impose highest strain, for example. Analyzing the differences in health effects of these two groups would be interesting, especially in the light of current reform efforts.

This study cannot perform an analysis of whether formal care is preferable over informal care. However, results suggest that the indirect costs of informal care should somehow enter a possible cost-benefit analysis when considering further reforms. Another limitation of this study is that we are only able to analyze the contemporaneous effect of the double burden on health. Schmitz and Westphal (2013) only find short-run negative mental health effects of careprovision while the medium-term effect is fairly small. This might well be the case for the double burden, too. Given, however, that the short-term effect of both working and caring is considerably larger than the one of just caring, it is not unlikely that this effect is longer lasting. Yet, this is left for future research.

[11] See http://www.bmg.bund.de/ministerium/presse/english-version/long-term-care/first-act-to-strengthen-long-term-care.html for a description of reform efforts, Date of access: 10/3/2014

2.7 Appendix

Table A2.1: SF-12v2 questionnaire in the SOEP

	Very Good	Good	Satis-factory	Poor	Bad
How would you describe your current health?					
	Greatly	Slightly	Not at all	–	–
When you ascend stairs, i.e. go up several floors on foot: Does your state of health affect you greatly, slightly or not at all?					
And what about having to cope with other tiring everyday tasks, i.e. where one has to lift something heavy or where one requires agility: Does your state of health affect you greatly, slightly or not at all?					
Please think about the last four weeks. How often did it occur within this period of time, . . .	Always	Often	Some-times	Almost never	Never
◇ that you felt rushed or pressed for time? ◇ that you felt run-down and melancholy? ◇ that you felt relaxed and well-balanced? ◇ that you used up a lot of energy? ◇ that you had strong physical pains? ◇ that due to physical health problems . . . you achieved less than you wanted to at work or in everyday tasks? . . . you were limited in some form at work or in everyday tasks? ◇ that due to mental health or emotional problems . . . you achieved less than you wanted to at work or in everyday tasks? . . . you carried out your work or everyday tasks less thoroughly than usual? ◇ that due to physical or mental health problems you were limited socially, i.e. in contact with friends, acquaintances or relatives?					

Note. Source: SOEP Individual question form. Available at http://panel.gsoep.de/soepinfo2008/.

Table A2.2: Descriptive Statistics

Variable	No Work, No Care	Care Only	Work Only	Double Burden
Pooled				
Age	46.662	52.043	43.803	49.258
Female	0.746	0.804	0.354	0.542
Married	0.726	0.812	0.637	0.751
Children in HH	0.416	0.247	0.346	0.220
Full-time	0.000	0.000	1.000	1.000
Education: Inadequate	0.026	0.016	0.010	0.011
Education: General	0.151	0.128	0.080	0.078
Education: Middle	0.529	0.539	0.445	0.431
Education: High School	0.070	0.048	0.072	0.066
Education: Voc. Training	0.064	0.093	0.091	0.102
Education: University	0.160	0.175	0.302	0.312
Foreign	0.103	0.047	0.066	0.025
Rural Area	0.261	0.294	0.253	0.339
Females				
Age	45.794	51.233	43.093	48.795
Married	0.767	0.824	0.538	0.729
Children in HH	0.487	0.283	0.247	0.169
Full-time	0.000	0.000	1.000	1.000
Education: Inadequate	0.025	0.015	0.011	0.006
Education: General	0.158	0.137	0.076	0.072
Education: Middle	0.520	0.542	0.428	0.436
Education: High School	0.077	0.055	0.095	0.085
Education: Voc. Training	0.064	0.090	0.075	0.059
Education: University	0.156	0.161	0.316	0.342
Foreign	0.100	0.044	0.060	0.032
Rural Area	0.252	0.292	0.259	0.326
Males				
Age	49.213	55.369	44.191	49.805
Married	0.604	0.764	0.691	0.778
Children in HH	0.207	0.103	0.400	0.280
Full-time	0.000	0.000	1.000	1.000
Education: Inadequate	0.030	0.023	0.009	0.018
Education: General	0.130	0.091	0.083	0.085
Education: Middle	0.554	0.529	0.454	0.425
Education: High School	0.051	0.019	0.060	0.045
Education: Voc. Training	0.064	0.106	0.099	0.153
Education: University	0.171	0.232	0.294	0.275
Foreign	0.110	0.061	0.071	0.018
Rural Area	0.285	0.300	0.250	0.355

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. Unconditional means for dependent and independent variables.

Table A2.3: MCS – Multinomial Logit for CLS-Choice – Coefficients

Controls	*Care Only*	*Work Only*	*Double Burden*
Plant Closure	−0.055	−1.335***	−1.365***
	(0.173)	(0.108)	(0.327)
Number of Siblings	−0.020	−0.008	−0.043
	(0.022)	(0.011)	(0.030)
Unemployment Rate (Female)	0.030	−0.032***	0.009
	(0.020)	(0.010)	(0.025)
Unemployment Rate (Male)	−0.042**	0.005	−0.023
	(0.020)	(0.009)	(0.024)
Nursing Care Places	−0.074**	−0.006	−0.062*
	(0.030)	(0.015)	(0.036)
Employees in Care	0.075**	−0.018	0.116***
	(0.034)	(0.017)	(0.042)
Age: 35-44	0.476***	0.291***	1.067***
	(0.162)	(0.047)	(0.192)
Age: 45-54	1.170***	0.039	1.495***
	(0.156)	(0.053)	(0.188)
Age: 55-64	1.240***	−1.319***	0.400*
	(0.156)	(0.061)	(0.204)
Marital Status	0.384***	−0.193***	0.173
	(0.096)	(0.044)	(0.113)
Children in HH	−0.341***	−0.788***	−1.085***
	(0.098)	(0.042)	(0.122)
Education: General	−0.009	0.361**	−0.128
	(0.302)	(0.172)	(0.453)
Education: Middle	0.103	0.670***	0.086
	(0.295)	(0.166)	(0.431)
Education: High School	−0.036	0.932***	0.608
	(0.343)	(0.177)	(0.464)
Education: voc. Train.	0.564*	1.150***	0.761*
	(0.318)	(0.175)	(0.449)
Education: University	0.110	1.527***	0.921**
	(0.303)	(0.169)	(0.435)
Foreign	−0.625***	−0.179**	−0.911***
	(0.192)	(0.070)	(0.298)
Rural Area	0.130	−0.022	0.138
	(0.111)	(0.052)	(0.127)
2006	−0.046	0.132***	0.063
	(0.084)	(0.036)	(0.105)
2008	−0.044	0.124***	0.103
	(0.098)	(0.043)	(0.123)
2010	−0.106	0.116***	−0.022
	(0.098)	(0.043)	(0.125)
Female	0.432***	−1.849***	−1.005***
	(0.093)	(0.039)	(0.094)
Constant	−3.813***	1.623***	−3.727***
	(0.418)	(0.202)	(0.576)
Federal State Dummies	YES	YES	YES

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Standard errors (clustered on individual level) in parentheses. N=35,982.

Table A2.4: Output - Multinomial Treatment Model - MCS

	Choice Equation			Outcome Equation
	Care Only	Work Only	Double Burden	MCS
Treatment Effects				
Care Only	–	–	–	-0.744
	–	–	–	(0.653)
Work Only	–	–	–	1.101***
	–	–	–	(0.403)
Double Burden	–	–	–	-4.946***
	–	–	–	(0.501)
No Work, No Care	*Reference Category*			
Instruments				
Plant Closure	-0.037	-1.547***	-1.395***	–
	(0.186)	(0.124)	(0.339)	–
Number of Siblings	-0.021	-0.008	-0.046	–
	(0.024)	(0.013)	(0.032)	–
Unempl. Rate (Female)	0.032	-0.038***	0.005	–
	(0.022)	(0.011)	(0.026)	–
Unempl. Rate (Male)	-0.045**	0.006	-0.019	–
	(0.021)	(0.011)	(0.026)	–
Nursing Care Places	-0.077**	-0.005	-0.067*	–
	(0.032)	(0.017)	(0.039)	–
Empl. in Care	0.080**	-0.025	0.122***	–
	(0.037)	(0.020)	(0.045)	–
Further Covariates				
Age: 35-44	0.482***	0.348***	1.102***	0.055
	(0.167)	(0.056)	(0.198)	(0.134)
Age: 45-54	1.220***	0.035	1.531***	0.363***
	(0.162)	(0.062)	(0.195)	(0.139)
Age: 55-64	1.340***	-1.542***	0.408*	1.578***
	(0.163)	(0.070)	(0.211)	(0.188)
Marital Status	0.406***	-0.219***	0.220*	0.682***
	(0.102)	(0.051)	(0.120)	(0.114)
Children in HH	-0.344***	-0.898***	-1.092***	0.097
	(0.105)	(0.049)	(0.128)	(0.120)
Education: General	-0.017	0.414**	-0.084	0.485
	(0.323)	(0.198)	(0.473)	(0.414)
Education: Middle	0.103	0.774***	0.140	0.937**
	(0.315)	(0.191)	(0.450)	(0.403)
Education: High Sch.	-0.051	1.077***	0.679	0.768*
	(0.366)	(0.205)	(0.484)	(0.433)
Education: voc. Train.	0.574*	1.336***	0.837*	0.818*
	(0.340)	(0.202)	(0.469)	(0.433)
Education: University	0.088	1.783***	1.018**	1.079***

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Table A2.4 – Continued

	(0.323)	(0.195)	(0.455)	(0.419)
Foreign	-0.662***	-0.203**	-0.946***	-0.255
	(0.203)	(0.082)	(0.304)	(0.176)
Rural Area	0.138	-0.031	0.154	0.030
	(0.119)	(0.061)	(0.133)	(0.126)
2006	-0.050	0.156***	0.072	0.045
	(0.090)	(0.042)	(0.109)	(0.128)
2008	-0.052	0.144***	0.119	0.127
	(0.105)	(0.050)	(0.129)	(0.118)
2010	-0.118	0.138***	-0.016	-0.402***
	(0.105)	(0.051)	(0.131)	(0.127)
Female	0.514***	-2.173***	-1.018***	-0.415**
	(0.097)	(0.045)	(0.099)	(0.175)
Constant	-4.368***	1.891***	-4.313***	22.989***
	(0.443)	(0.234)	(0.600)	(0.604)
MCS_{t-1}	–	–	–	0.494***
	–	–	–	(0.006)
Federal State Dummies	YES	YES	YES	YES
Selection Effects				
lnalpha	–	–	–	1.988***
	–	–	–	(0.033)
λ Care Only	–	–	–	-0.552
	–	–	–	(0.656)
λ Work Only	–	–	–	-0.881*
	–	–	–	(0.468)
λ Double Burden	–	–	–	4.020***
	–	–	–	(0.438)
N	35,982	35,982	35,982	35,982

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.5; * p<0.1. Standard errors in parentheses.

Table A2.5: Output - Multinomial Treatment Model - MCS-Female

	Choice Equation			Outcome Equation
	Care Only	Work Only	Double Burden	MCS
Treatment Effects				
Care Only	–	–	–	-3.243***
	–	–	–	(0.985)
Work Only	–	–	–	1.113**
	–	–	–	(0.432)
Double Burden	–	–	–	-5.777***
	–	–	–	(0.668)
No Work, No Care	*Reference Category*			
Instruments				
Plant Closure	0.094	-1.083***	-1.720***	–
	(0.233)	(0.176)	(0.601)	–
Number of Siblings	-0.006	-0.011	-0.045	–
	(0.028)	(0.018)	(0.042)	–
Unempl. Rate (Female)	0.031	-0.046***	0.013	–
	(0.025)	(0.015)	(0.034)	–
Unempl. Rate (Male)	-0.041*	0.026*	-0.015	–
	(0.024)	(0.015)	(0.033)	–
Nursing Care Places	-0.102***	-0.018	-0.033	–
	(0.037)	(0.024)	(0.051)	–
Empl. in Care	0.105**	-0.016	0.084	–
	(0.043)	(0.028)	(0.062)	–
Further Covariates				
Age: 35-44	0.516***	0.275***	1.238***	0.181
	(0.183)	(0.074)	(0.274)	(0.189)
Age: 45-54	1.212***	-0.246***	1.455***	0.973***
	(0.180)	(0.084)	(0.266)	(0.197)
Age: 55-64	1.333***	-1.656***	0.358	2.043***
	(0.186)	(0.092)	(0.286)	(0.258)
Marital Status	0.310***	-0.842***	-0.110	1.075***
	(0.116)	(0.063)	(0.155)	(0.169)
Children in HH	-0.388***	-1.832***	-1.745***	0.423**
	(0.120)	(0.070)	(0.186)	(0.202)
Education: General	0.063	0.146	0.453	1.053*
	(0.365)	(0.270)	(0.827)	(0.557)
Education: Middle	0.159	0.600**	0.846	1.827***
	(0.355)	(0.258)	(0.796)	(0.544)
Education: High Sch.	0.087	1.031***	1.560*	1.487**
	(0.407)	(0.273)	(0.830)	(0.585)
Education: voc. Train.	0.640*	1.087***	1.129	1.828***
	(0.386)	(0.276)	(0.827)	(0.589)
Education: University	0.101	1.598***	1.777**	1.941***

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Table A2.5 – Continued

	(0.366)	(0.263)	(0.799)	(0.562)
Foreign	-0.722***	-0.089	-0.526	-0.235
	(0.230)	(0.123)	(0.392)	(0.254)
Rural Area	0.116	-0.043	-0.067	0.089
	(0.137)	(0.083)	(0.172)	(0.176)
2006	0.013	0.173***	0.053	-0.039
	(0.101)	(0.056)	(0.143)	(0.182)
2008	0.045	0.253***	0.032	0.074
	(0.118)	(0.069)	(0.173)	(0.169)
2010	-0.054	0.195***	-0.007	-0.531***
	(0.118)	(0.069)	(0.176)	(0.183)
Constant	-3.970***	0.430	-5.883***	21.705***
	(0.487)	(0.317)	(1.012)	(0.735)
MCS_{t-1}	–	–	–	0.486***
	–	–	–	(0.008)
Federal State Dummies	YES	YES	YES	YES
Selection Effects				
lnalpha	–	–	–	1.945***
	–	–	–	(0.043)
λ Care Only	–	–	–	1.812*
	–	–	–	(1.042)
λ Work Only	–	–	–	-1.202***
	–	–	–	(0.475)
λ Double Burden	–	–	–	4.658***
	–	–	–	(0.566)
N	18,885	18,885	18,885	18,885

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.5; * p<0.1. Standard errors in parentheses.

Table A2.6: Output - Multinomial Treatment Model - MCS - Male

	Choice Equation			Outcome Equation
	Care Only	Work Only	Double Burden	MCS
Treatment Effects				
Care Only	–	–	–	1.543*
	–	–	–	(0.902)
Work Only	–	–	–	1.884***
	–	–	–	(0.560)
Double Burden	–	–	–	-3.897***
	–	–	–	(0.655)
No Work, No Care	*Reference Category*			
Instruments				
Plant Closure	-0.367	-2.026***	-1.425***	–
	(0.325)	(0.154)	(0.419)	–
Number of Siblings	-0.082*	-0.027	-0.063	–
	(0.045)	(0.019)	(0.048)	–
Unempl. Rate (Female)	0.044	-0.025	0.001	–
	(0.044)	(0.017)	(0.039)	–
Unempl. Rate (Male)	-0.064	-0.025	-0.036	–
	(0.044)	(0.015)	(0.039)	–
Nursing Care Places	0.019	0.014	-0.096	–
	(0.062)	(0.027)	(0.059)	–
Empl. in Care	-0.013	-0.043	0.152**	–
	(0.066)	(0.030)	(0.065)	–
Further Covariates				
Age: 35-44	0.080	0.537***	1.035***	-0.102
	(0.431)	(0.094)	(0.289)	(0.189)
Age: 45-54	1.133***	0.121	1.466***	-0.072
	(0.365)	(0.098)	(0.289)	(0.197)
Age: 55-64	1.194***	-1.596***	0.298	1.615***
	(0.338)	(0.100)	(0.314)	(0.265)
Marital Status	0.515**	0.599***	0.766***	0.274
	(0.206)	(0.079)	(0.190)	(0.168)
Children in HH	-0.521*	0.251***	0.029	-0.075
	(0.281)	(0.083)	(0.184)	(0.156)
Education: General	-0.426	0.721**	-0.370	-0.269
	(0.677)	(0.304)	(0.621)	(0.606)
Education: Middle	-0.120	1.013***	-0.306	-0.268
	(0.661)	(0.292)	(0.586)	(0.588)
Education: High Sch.	-0.864	1.143***	-0.065	-0.194
	(0.906)	(0.317)	(0.650)	(0.635)
Education: voc. Train.	0.285	1.627***	0.687	-0.437
	(0.699)	(0.313)	(0.613)	(0.628)
Education: University	-0.011	1.934***	0.432	-0.124

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Table A2.6 – Continued

	(0.669)	(0.299)	(0.600)	(0.607)
Foreign	-0.377	-0.471***	-1.675***	-0.257
	(0.405)	(0.123)	(0.422)	(0.247)
Rural Area	0.179	0.058	0.423**	-0.039
	(0.245)	(0.097)	(0.206)	(0.177)
2006	-0.331	0.126*	0.080	0.164
	(0.202)	(0.068)	(0.171)	(0.180)
2008	-0.420*	0.004	0.177	0.208
	(0.235)	(0.080)	(0.197)	(0.163)
2010	-0.339	0.051	-0.049	-0.247
	(0.230)	(0.082)	(0.202)	(0.174)
Constant	-3.585***	1.429***	-3.772***	23.501***
	(0.896)	(0.349)	(0.773)	(0.835)
MCS_{t-1}	–	–	–	0.499***
	–	–	–	(0.009)
Federal State Dummies	YES	YES	YES	YES
Selection Effects				
lnalpha	–	–	–	1.932***
	–	–	–	(0.044)
λ Care Only	–	–	–	-1.786***
	–	–	–	(0.664)
λ Work Only	–	–	–	-1.018
	–	–	–	(0.640)
λ Double Burden	–	–	–	3.663***
	–	–	–	(0.524)
N	17,097	17,097	17,097	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.5; * p<0.1. Standard errors in parentheses.

Table A2.7: Output - Multinomial Treatment Model - PCS

	Choice Equation			Outcome Equation
	Care Only	Work Only	Double Burden	MCS
Treatment Effects				
Care Only	–	–	–	0.258
	–	–	–	(0.361)
Work Only	–	–	–	1.552***
	–	–	–	(0.413)
Double Burden	–	–	–	-2.143***
	–	–	–	(0.475)
No Work, No Care	*Reference Category*			
Instruments				
Plant Closure	-0.045	-1.550***	-1.373***	–
	(0.187)	(0.124)	(0.332)	–
Number of Siblings	-0.021	-0.009	-0.046	–
	(0.024)	(0.013)	(0.032)	–
Unempl. Rate (Female)	0.032	-0.038***	0.011	–
	(0.022)	(0.011)	(0.026)	–
Unempl. Rate (Male)	-0.044**	0.007	-0.025	–
	(0.021)	(0.011)	(0.026)	–
Nursing Care Places	-0.076**	-0.004	-0.069*	–
	(0.033)	(0.017)	(0.039)	–
Empl. in Care	0.079**	-0.026	0.127***	–
	(0.037)	(0.020)	(0.044)	–
Further Covariates				
Age: 35-44	0.483***	0.348***	1.103***	-1.087***
	(0.166)	(0.056)	(0.198)	(0.101)
Age: 45-54	1.219***	0.034	1.535***	-2.055***
	(0.162)	(0.062)	(0.195)	(0.106)
Age: 55-64	1.341***	-1.543***	0.400*	-3.049***
	(0.163)	(0.070)	(0.212)	(0.163)
Marital Status	0.407***	-0.220***	0.203*	-0.231***
	(0.102)	(0.051)	(0.120)	(0.089)
Children in HH	-0.343***	-0.898***	-1.099***	0.752***
	(0.105)	(0.049)	(0.128)	(0.100)
Education: General	-0.021	0.412**	-0.096	0.198
	(0.325)	(0.198)	(0.472)	(0.308)
Education: Middle	0.102	0.772***	0.118	1.043***
	(0.318)	(0.191)	(0.448)	(0.299)
Education: High Sch.	-0.054	1.074***	0.653	1.340***
	(0.368)	(0.205)	(0.483)	(0.321)
Education: voc. Train.	0.568*	1.333***	0.826*	1.012***
	(0.342)	(0.202)	(0.467)	(0.324)
Education: University	0.086	1.780***	0.998**	1.957***

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Table A2.7 – Continued

	(0.326)	(0.195)	(0.453)	(0.319)
Foreign	-0.664***	-0.203**	-0.956***	-0.334**
	(0.203)	(0.082)	(0.304)	(0.141)
Rural Area	0.138	-0.029	0.150	-0.359***
	(0.119)	(0.061)	(0.134)	(0.100)
2006	-0.051	0.158***	0.072	-0.431***
	(0.090)	(0.042)	(0.110)	(0.105)
2008	-0.050	0.148***	0.105	-0.234**
	(0.105)	(0.050)	(0.130)	(0.097)
2010	-0.116	0.140***	-0.024	-0.461***
	(0.105)	(0.051)	(0.131)	(0.103)
Female	0.516***	-2.172***	-1.010***	0.418**
	(0.097)	(0.045)	(0.099)	(0.163)
Constant	-4.364***	1.898***	-4.300***	20.783***
	(0.447)	(0.234)	(0.597)	(0.539)
PCS_{t-1}	–	–	–	0.581***
	–	–	–	(0.006)
Federal State Dummies	YES	YES	YES	YES
Selection Effects				
lnalpha	–	–	–	1.809***
	–	–	–	(0.039)
λ Care Only	–	–	–	-0.611**
	–	–	–	(0.310)
λ Work Only	–	–	–	-0.801*
	–	–	–	(0.485)
λ Double Burden	–	–	–	2.838***
	–	–	–	(0.443)
N	35,982	35,982	35,982	35,982

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.5; * p<0.1. Standard errors in parentheses.

Table A2.8: Output - Multinomial Treatment Model - PCS-Female

	Choice Equation			Outcome Equation
	Care Only	Work Only	Double Burden	MCS
Treatment Effects				
Care Only	–	–	–	0.063
	–	–	–	(0.600)
Work Only	–	–	–	1.808***
	–	–	–	(0.490)
Double Burden	–	–	–	-2.327***
	–	–	–	(0.673)
No Work, No Care	*Reference Category*			
Instruments				
Plant Closure	0.090	-1.094***	-1.705***	–
	(0.232)	(0.179)	(0.572)	–
Number of Siblings	-0.006	-0.013	-0.045	–
	(0.028)	(0.018)	(0.043)	–
Unempl. Rate (Female)	0.029	-0.046***	0.012	–
	(0.025)	(0.015)	(0.035)	–
Unempl. Rate (Male)	-0.040*	0.027*	-0.016	–
	(0.024)	(0.015)	(0.034)	–
Nursing Care Places	-0.100***	-0.014	-0.044	–
	(0.038)	(0.024)	(0.052)	–
Empl. in Care	0.103**	-0.021	0.096	–
	(0.044)	(0.028)	(0.062)	–
Further Covariates				
Age: 35-44	0.516***	0.275***	1.257***	-0.963***
	(0.183)	(0.074)	(0.275)	(0.140)
Age: 45-54	1.213***	-0.244***	1.459***	-1.773***
	(0.180)	(0.084)	(0.268)	(0.156)
Age: 55-64	1.333***	-1.655***	0.361	-2.656***
	(0.186)	(0.092)	(0.288)	(0.240)
Marital Status	0.305***	-0.842***	-0.136	-0.040
	(0.116)	(0.063)	(0.155)	(0.141)
Children in HH	-0.392***	-1.832***	-1.757***	1.297***
	(0.120)	(0.070)	(0.186)	(0.190)
Education: General	0.067	0.141	0.475	0.696*
	(0.364)	(0.269)	(0.837)	(0.388)
Education: Middle	0.163	0.592**	0.852	1.796***
	(0.354)	(0.257)	(0.806)	(0.377)
Education: High Sch.	0.091	1.022***	1.565*	1.919***
	(0.407)	(0.272)	(0.841)	(0.408)
Education: voc. Train.	0.646*	1.079***	1.129	1.417***
	(0.385)	(0.275)	(0.836)	(0.417)
Education: University	0.103	1.590***	1.782**	2.332***

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Table A2.8 – Continued

	(0.365)	(0.261)	(0.808)	(0.400)
Foreign	-0.726***	-0.091	-0.506	-0.301
	(0.231)	(0.123)	(0.392)	(0.197)
Rural Area	0.118	-0.041	-0.050	-0.260*
	(0.137)	(0.083)	(0.173)	(0.140)
2006	0.025	0.177***	0.057	-0.384***
	(0.101)	(0.056)	(0.145)	(0.149)
2008	0.052	0.258***	0.033	-0.259*
	(0.119)	(0.069)	(0.174)	(0.137)
2010	-0.051	0.201***	-0.017	-0.349**
	(0.119)	(0.070)	(0.176)	(0.147)
Constant	-3.967***	0.442	-5.897***	20.229***
	(0.488)	(0.315)	(1.022)	(0.638)
PCS_{t-1}	–	–	–	0.576***
	–	–	–	(0.008)
Federal State Dummies	YES	YES	YES	YES
Selection Effects				
lnalpha	–	–	–	1.832***
	–	–	–	(0.049)
λ Care Only	–	–	–	-0.452
	–	–	–	(0.609)
λ Work Only	–	–	–	-1.592***
	–	–	–	(0.558)
λ Double Burden	–	–	–	2.659***
	–	–	–	(0.620)
N	18,885	18,885	18,885	18,885

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.5; * p<0.1. Standard errors in parentheses.

Table A2.9: Output - Multinomial Treatment Model - PCS - Male

	Choice Equation			Outcome Equation
	Care Only	Work Only	Double Burden	MCS
Treatment Effects				
Care Only	–	–	–	-0.650
	–	–	–	(1.021)
Work Only	–	–	–	2.581***
	–	–	–	(0.586)
Double Burden	–	–	–	-1.016
	–	–	–	(0.772)
No Work, No Care	*Reference Category*			
Instruments				
Plant Closure	-0.353	-2.024***	-1.387***	–
	(0.325)	(0.154)	(0.410)	–
Number of Siblings	-0.084*	-0.028	-0.063	–
	(0.045)	(0.019)	(0.048)	–
Unempl. Rate (Female)	0.045	-0.028*	0.014	–
	(0.044)	(0.017)	(0.039)	–
Unempl. Rate (Male)	-0.064	-0.022	-0.048	–
	(0.044)	(0.016)	(0.039)	–
Nursing Care Places	0.016	0.012	-0.091	–
	(0.063)	(0.027)	(0.059)	–
Empl. in Care	-0.011	-0.043	0.149**	–
	(0.067)	(0.030)	(0.064)	–
Further Covariates				
Age: 35-44	0.093	0.536***	1.025***	-1.334***
	(0.432)	(0.094)	(0.288)	(0.146)
Age: 45-54	1.148***	0.120	1.476***	-2.306***
	(0.365)	(0.098)	(0.287)	(0.153)
Age: 55-64	1.205***	-1.597***	0.277	-3.104***
	(0.338)	(0.100)	(0.315)	(0.240)
Marital Status	0.498**	0.600***	0.759***	-0.425***
	(0.206)	(0.079)	(0.190)	(0.136)
Children in HH	-0.515*	0.249***	0.016	0.281**
	(0.281)	(0.083)	(0.184)	(0.131)
Education: General	-0.438	0.720**	-0.366	-0.619
	(0.675)	(0.303)	(0.612)	(0.502)
Education: Middle	-0.148	1.010***	-0.313	-0.109
	(0.657)	(0.291)	(0.578)	(0.484)
Education: High Sch.	-0.891	1.139***	-0.089	0.316
	(0.905)	(0.316)	(0.642)	(0.516)
Education: voc. Train.	0.246	1.621***	0.706	0.148
	(0.694)	(0.312)	(0.604)	(0.511)
Education: University	-0.042	1.929***	0.437	1.094**

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Table A2.9 – Continued

	(0.665)	(0.299)	(0.590)	(0.508)
Foreign	-0.362	-0.471***	-1.684***	-0.200
	(0.407)	(0.123)	(0.422)	(0.202)
Rural Area	0.176	0.060	0.413**	-0.493***
	(0.246)	(0.097)	(0.210)	(0.143)
2006	-0.334*	0.133*	0.074	-0.501***
	(0.203)	(0.069)	(0.172)	(0.149)
2008	-0.418*	0.011	0.161	-0.229*
	(0.237)	(0.081)	(0.198)	(0.137)
2010	-0.337	0.055	-0.049	-0.620***
	(0.231)	(0.082)	(0.202)	(0.143)
Constant	-3.532***	1.447***	-3.770***	21.530***
	(0.889)	(0.349)	(0.758)	(0.774)
PCS_{t-1}	–	–	–	0.579***
	–	–	–	(0.009)
Federal State Dummies	YES	YES	YES	YES
Selection Effects				
lnalpha	–	–	–	1.786***
	–	–	–	(0.067)
λ Care Only	–	–	–	0.294
	–	–	–	(0.963)
λ Work Only	–	–	–	-0.990
	–	–	–	(0.696)
λ Double Burden	–	–	–	2.631***
	–	–	–	(0.765)
N	17,097	17,097	17,097	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.5; * p<0.1. Standard errors in parentheses.

Table A2.10: Robustness Check – MCS – No siblings as exclusion restrictions

	Pooled	Female	Male
Care Only	-0.734	-3.240^{***}	1.553^{*}
	(0.657)	(0.981)	(0.901)
Work Only	1.111^{***}	1.119^{***}	1.942^{***}
	(0.402)	(0.431)	(0.580)
Double Burden	-4.943^{***}	-5.778^{***}	-3.868^{***}
	(0.502)	(0.666)	(0.662)
No Work, No Care	*Reference Category*		
MCS_{t-1}	0.494^{***}	0.486^{***}	0.499^{***}
	(0.006)	(0.008)	(0.009)
Constant	22.981^{***}	21.701^{***}	23.467^{***}
	(0.603)	(0.735)	(0.840)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
lnalpha	1.988^{***}	1.945^{***}	1.933^{***}
	(0.033)	(0.043)	(0.044)
$\lambda_{CareOnly}$	-0.564	1.809^{*}	-1.794^{***}
	(0.661)	(1.038)	(0.663)
$\lambda_{WorkOnly}$	-0.894^{*}	-1.210^{**}	-1.088^{*}
	(0.466)	(0.473)	(0.666)
$\lambda_{DoubleBurden}$	4.016^{***}	4.657^{***}	3.633^{***}
	(0.439)	(0.564)	(0.537)
N	35,982	18,885	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Standard errors (clustered on individual level) in parentheses.

Table A2.11: Robustness Check – PCS – No siblings as exclusion restrictions

	Pooled	Female	Male
Care Only	0.242	−0.058	−0.636
	(0.362)	(0.590)	(0.995)
Work Only	1.527***	1.762***	2.567***
	(0.415)	(0.498)	(0.598)
Double Burden	−2.125***	−2.318***	−0.974
	(0.482)	(0.674)	(0.820)
No Work, No Care	*Reference Category*		
PCS_{t-1}	0.581***	0.576***	0.579***
	(0.006)	(0.008)	(0.009)
Constant	20.801***	20.254***	21.537***
	(0.540)	(0.640)	(0.778)
Socio-Economic Controls	YES	YES	YES
Federal State Dummies	YES	YES	YES
Year Dummies	YES	YES	YES
lnalpha	1.812***	1.835***	1.789***
	(0.040)	(0.049)	(0.070)
$\lambda_{CareOnly}$	−0.595*	−0.448	0.279
	(0.310)	(0.597)	(0.933)
$\lambda_{WorkOnly}$	−0.771	−1.536***	−0.972
	(0.487)	(0.568)	(0.711)
$\lambda_{DoubleBurden}$	2.817***	2.646***	2.584***
	(0.451)	(0.621)	(0.823)
N	35,982	18,885	17,097

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses.

Table A2.12: Robustness Check: Care Provision at least 2h per day

	MCS	PCS
Care Only	-1.779^{**}	-0.013
	(0.742)	(0.403)
Work Only	0.542	0.902^{***}
	(0.385)	(0.322)
Double Burden	-4.569^{***}	-1.294
	(0.839)	(0.889)
No Work, No Care	*Reference Category*	
Dependent Variable$_{t-1}$	0.495^{***}	0.582^{***}
	(0.006)	(0.006)
Constant	23.371^{***}	21.243^{***}
	(0.591)	(0.508)
Socio-Economic Controls	YES	YES
Federal State Dummies	YES	YES
Year Dummies	YES	YES
lnalpha	2.040^{***}	1.894^{***}
	(0.036)	(0.025)
$\lambda_{CareOnly}$	-0.162	-0.300
	(0.700)	(0.307)
$\lambda_{WorkOnly}$	-0.227	0.010
	(0.442)	(0.370)
$\lambda_{DoubleBurden}$	3.320^{***}	1.332
	(0.655)	(0.782)
N	35,982	35,982

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses. CLS-sizes: NoWorkNoCare 14,320; CareOnly 750; WorkOnly 20,635; DoubleBurden 277

Table A2.13: Robustness Check: Full-time Work 6h/day

	MCS	PCS
Care Only	-0.751	0.138
	(0.782)	(0.385)
Work Only	1.199***	1.311***
	(0.408)	(0.391)
Double Burden	-4.855***	-2.001***
	(0.511)	(0.548)
No Work, No Care		Reference Category
Dependent Variable$_{t-1}$	0.494***	0.582***
	(0.006)	(0.006)
Constant	22.957***	20.982***
	(0.599)	(0.524)
Socio-Economic Controls	YES	YES
Federal State Dummies	YES	YES
Year Dummies	YES	YES
lnalpha	1.983***	1.822***
	(0.036)	(0.043)
$\lambda_{CareOnly}$	-0.549	-0.585*
	(0.787)	(0.326)
$\lambda_{WorkOnly}$	-0.919**	-0.542
	(0.476)	(0.462)
$\lambda_{DoubleBurden}$	4.095***	2.729***
	(0.477)	(0.549)
N	35,982	35,982

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses.

Table A2.14: Robustness Check: Full-time Work 8h/day

	MCS	PCS
Care Only	-0.711	0.332
	(0.633)	(0.340)
Work Only	1.206***	1.576***
	(0.419)	(0.405)
Double Burden	-5.233***	-2.297***
	(0.476)	(0.457)
No Work, No Care		Reference Category
Dependent Variable$_{t-1}$	0.494***	0.583***
	(0.006)	(0.006)
Constant	22.920***	20.703***
	(0.612)	(0.538)
Socio-Economic Controls	YES	YES
Federal State Dummies	YES	YES
Year Dummies	YES	YES
lnalpha	1.978***	1.805***
	(0.032)	(0.038)
$\lambda_{CareOnly}$	-0.539	-0.721**
	(0.631)	(0.288)
$\lambda_{WorkOnly}$	-1.100**	-0.955**
	(0.487)	(0.473)
$\lambda_{DoubleBurden}$	4.111***	2.829***
	(0.404)	(0.421)
N	35,982	35,982

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses.

Table A2.15: Robustness Check – No Lagged Dependent Variable

	MCS	PCS
Care Only	-0.907	-0.104
	(0.705)	(0.482)
Work Only	2.535***	3.122***
	(0.534)	(0.616)
Double Burden	-7.418***	-3.691***
	(0.513)	(0.556)
No Work, No Care	*Reference Category*	
Dep. Variable$_{t-1}$	–	–
	–	–
Constant	45.232***	50.136***
	(0.773)	(0.731)
Socio-Economic Controls	YES	YES
Federal State Dummies	YES	YES
Year Dummies	YES	YES
lnalpha	1.955***	1.868***
	(0.045)	(0.065)
$\lambda_{CareOnly}$	-1.212*	-0.642*
	(0.666)	(0.345)
$\lambda_{WorkOnly}$	-2.023***	-1.172*
	(0.614)	(0.720)
$\lambda_{DoubleBurden}$	6.194***	5.036***
	(0.362)	(0.480)
N	35,982	35,982

Note: Authors' calculations based on the SOEP for the years 2004, 2006, 2008 and 2010. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on individual level) in parentheses.

3 Risk-Loving in the End? The Role of Option Values in Choosing Risky and Marginally Effective Treatments

3.1 Introduction

Health economics literature indicates that a substantial part of health care expenditure is induced in the last year of the patients' lives (Ginzberg, 1980; Scitovsky, 1984; Lubitz and Riley, 1993; Felder et al., 2000; Hogan et al., 2001; Riley and Lubitz, 2010) and the proximity to death is found to be a relevant determinant of health care expenditures ((see e.g. Werblow et al., 2007; Felder et al., 2010; Wong et al., 2011); for an overview of literature on the relationship between time to death, aging and health care expenditures see Payne et al. (2007)). Apart from expensive long-term care, the reason for this pattern may to a large extent be accredited to two factors: Intensive care after injuries and end-of-life treatments of fatal diseases. While the former is usually the consequence of sudden impacts such as accidents, there is no deliberate decision-making of patients involved. The latter, however, involves a process of choosing between different treatment options. End-of-life treatments are usually not only (very) expensive but frequently involve high risk. Moreover they are often only marginally effective. Marginal effectiveness has more than one dimension. First, a treatment can be seen as being marginally effective, if its response rate is low. That is, for a single patient, the treatment might well improve medical conditions, but the overall effect across all treated patients is small. Second, a treatment is marginally effective if it per se

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has only very small effects in terms of prolonging the terminally ill patients' lives. Both dimensions are highly relevant in terms of cost effectiveness: For the first one, few successful cases have to be counted against many unsuccessful ones; for the second one, even successful treatments have only marginal effects.
As a useful example, one might think of chemotherapies, which often not only prolong the patient's life for a short period but also have a rather low response rate (e.g. Shepherd et al., 2005). This shows, that both dimensions can hardly be disentangled, as treatments may well accommodate both dimensions. However, a majority of cancer patients is treated by chemotherapy at some stage (see e.g. Deutsche Krebshilfe e.V., 2011). This increases health care expenditures as not only the single treatments are very expensive, but also the prevalence of cancer in western societies is high (American Cancer Society, 2011, 2014). Besides the fact that many of those treatments are administered, technical and medical progress in diagnosing and treating diseases increases the spending for terminal care further. That is, the new treatments increase expenses by providing new possibilities to treat diseases which could not have been treated before and by having high innovation costs (Newhouse, 1992; Okunade and Murthy, 2002; Meropol and Schulman, 2007). There might even be a further channel over which medical progress raises health care expenditures even before its approval, by inducing an option value for terminally ill patients which stimulates demand for marginally effective treatments.
Philipson et al. (2010) claim that "factors that increase the rate of future innovation will also increase the demand for terminal care" and further "the option value of future cures may also lead one to predict a risk-loving behavior when deciding between treatments with different survival distributions". In the light of this statement and the observation of rising health care expenditures, it is crucial to have rules of how to allocate limited resources. Against this background, marginally effective treatments are targeted as offering large savings potential for social insurers and as such should be used as a criterion to posteriorize. The reasoning behind that is - from an ethical point of view - it might be preferable, to accept rather small sacrifices from a large group of patients than large sacrifices from a few small groups (Buyx et al., 2009). Hence, expensive treatments which offer only small benefits, in any of the two dimensions, might be a point of vantage.
From a health economics perspective, it is interesting to investigate the preferences that drive the demand for marginally effective treatments in end-of-life situations to contribute to the prioritization debate. As in countries with full statutory health insurance, costs play a minor role for the patients themselves other factors must

influence demand. Here, risk preferences may be crucial factors for the assessment of different treatment options.
Personal perceptions about future treatments and about potential research breakthroughs might become important when it comes to assessing treatments with different survival distributions. This makes it crucial not only to understand patients' willingness to pay but also their willingness to dare. Why are people willing to take health-risks at the end of their lives? What are the consequences for health policy and prioritization in health care?
Based on related work by Philipson et al. (2010), I analyse the treatment choice behavior by employing a Discrete Choice Experiment (DCE) featuring two mutually exclusive treatment alternatives with varying survival distributions. Further, I introduce an attribute that creates an option value of future cures. By this approach, it can be investigated whether the option value of a potential future cure shifts preferences towards risky and marginally effective treatments. The results suggest that individuals are risk-averse with respect to remaining lifetime, ceteris paribus. In the presence of option values of future cures, however, the preferences shift towards higher risk acceptance. That is, individuals take a high risk of immediate death, if there is a prospect of prolongation of life by benefiting from a potential future cure. This result even holds for a subsample of persons identified as risk-averse by a Holt and Laury (2002)-type lottery approach.
The paper is organized as follows: Section 3.2 shortly explains the general framework of DCEs and the empirical model employed in the estimation. In section 3.3, I describe the DCE used in the analysis of treatment choice behavior before I present the results in section 3.4. Section 3.5 concludes.

3.2 DCE Framework and Empirical Strategy

Discrete choice experiments are a stated choice method that is based on the understanding, "that it is the properties or characteristics of the goods, from which utility is derived" (Lancaster, 1966). In a DCE, the participants are repeatedly asked to decide for one of at least two competing alternatives. The alternatives are described by attributes which characteristics vary across certain levels along the experiment. The researcher exploits this variation by applying econometric techniques in order to gain insights about an underlying utility function. This approach has the advantage of only subtly eliciting the preference ordering of individuals, which decreases the assumptions about the cognitive abilities of participants (Louviere et al., 2000). As such, DCEs are widely applied in various fields of economic research such as transportation (Hensher, 1994), environmental (Hoyos, 2010) and health economics (for an overview see de Bekker-Grob et al. (2012)). As random utility theory (Thurstone, 1927; McFadden, 1974) serves as basis , DCEs start from the assumption, that the utility of an alternative i for an individual n (U_{in})can be described by an observable part (V_{in}) and an unobservable part (ϵ_{in}) which are additive and independent:

$$U_{in} = V_{in} + \epsilon_{in} \tag{3.1}$$

The observable component is a function of the vector including all combinations of attribute levels $V_{in} = V_{in}(x_{in})$. Most often it is seen as being a linear function of the weighted attributes entering the utility function:

$$V_{in} = \beta_{0i} + \beta_{1i} f(x_{1in}) + \beta_{2i} f(x_{2in}) + \beta_{3i} f(x_{3in}) + ... + \beta_{Ki} f(x_{Kin}) \tag{3.2}$$

β_{ki} is the weight for the alternative i and the attribute k.
β_{0i} is the alternative-specific constant, representing unobservable sources of utility.

To construct a choice model, one needs to assume rational and utility maximizing individuals. Respondents compare utilities of each alternative and choose the one yielding the highest personal utility. Hence, the probability that one alternative has the highest utility equals the probability that the respective alternative is the chosen one (Louviere et al., 2000). Hereby, both parts of utilitiy V_{in} and ϵ_{in} play a role in decision making. As a consequence, the actual choices of respondents can be explained as probabilities since ϵ_{in} is subject to chance from the point of view of a researcher. The probability that a subject n chooses the alternative i then is:

$$\begin{aligned} Prob_{in} &= Prob(U_{in} \geq U_{jn}) \forall j \in j = 1, ..., J; i \neq j \\ Prob_{in} &= Prob\left[(V_{in} + \epsilon_{in}) \geq (V_{jn} + \epsilon_{jn}) \forall j \in j = 1, ..., J; i \neq j\right] \\ Prob_{in} &= Prob\left[(\epsilon_{jn} - \epsilon_{in}) \leq (V_{in} - V_{jn}) \forall j \in j = 1, ..., J; i \neq j\right] \end{aligned} \tag{3.3}$$

The multinomial logit model (MNL) has become the most commonly used method in analyzing DCEs (de Bekker-Grob et al., 2012; Hensher et al., 2005; Louviere et al., 2000). As it ignores preference heterogeneity across respondents and imposes the crucial independence of irrelevant alternatives assumption, more sophisticated models recently gain importance in analysing choice data. As I suspect heterogeneity in preferences, I allow parameters to vary across respondents by fitting a mixed logit model.[1] The mixed logit model has become increasingly popular as it does not impose the restrictive independence of irrelevant alternatives assumption and accounts for preference heterogeneity (de Bekker-Grob et al., 2012). To capture the heterogeneity in preferences η_n is included in the observable part of utility. η_n accounts for individual deviations from the estimated mean (Revelt and Train, 1998).

$$U_{in} = (\beta + \eta_n)x_{in} + \epsilon_{in} \tag{3.4}$$

I use the mixlogit stata routine to estimate the following mixed logit model (Hole, 2007b):

$$Prob_{in}(i|\theta) = \int \frac{exp(V_{in})}{\sum_{j=1}^{J} exp(V_{jn})} f(\beta_n|\theta)d(\beta_n) \qquad \forall j \in j = 1, ..., J; i \neq j, \tag{3.5}$$

where θ stands for the estimated coefficients and their standard deviations and $f(\beta_n|\theta)$ describes the density functions of the vector of parameters which enter the indirect utility functions.

3.3 Methods

The aim of the study is to investigate risk preferences of individuals when choosing marginally effective treatments in the presence of an option value, which potentially induce hidden costs. A DCE is conducted to investigate the preference structure of respondents that choose between treatments with different survival distributions.

3.3.1 Setting

This study draws upon a paper by Philipson et al. (2010) in which the authors claim that patients might exhibit risk-loving behavior in treatment choice when near death. They argue that information on new medical therapies, which are about to be introduced at some point in the future, will not only lead to risk-loving behavior when choosing therapies but also increase the demand for terminal care that already is available. The argument is that the sole prospect of possible future cures might induce a positive option value for patients today. The option value

[1]Note, following the reasoning in Train (2000) I fix the co-payment parameters. This approach resolves distributional issues of estimated willingness to pay and problems of instability of mixed logit models when all parameters are allowed to vary.

increases, if factors that positively influence the probability or quality of future cures increase. Especially the option value might increase in factors such as drugs entering the final phase of approval or high investments in technology.[2] However, an increase in the option value is based on personal perceptions and as such might also well be based on rumors, insufficient information or vague media reports and need not necessarily to be scientifically grounded. Such an option value may induce patients to prefer risky treatments that offer the insecure chance to live for longer time span, over safe treatments with identical expected values. In line with the argument of Philipson et al. (2010), the hypothesis is that patients in end-of-life situations might become risk-loving if they perceive a chance to benefit from the future cure by choosing a risky first-line treatment. In consequence, the demand for such first-line therapies should also increase even though it might involve risk. In this respect, the main aim of this DCE-study is to investigate whether individuals actually exhibit risk-loving behavior and high demand for marginally effective end-of-life treatments when there is an option value.

I design the DCE to include two competing alternatives which are labeled *First-Line Treatment* and *No Treatment*. Each of the two alternatives is described by four attributes with varying levels. The respondents are asked to imagine a scenario in which they suffer from cancer and are offered a first-line treatment. Further, they are given the information that there might be a new therapy introduced at some point in the future. Terminal cancer serves to frame the hypothetical setting, as cancer is a widespread disease which causes high costs to society (American Cancer Society, 2014). Most respondents are believed to know someone in their wider social environment who suffers from cancer. Thus, the choice of cancer as an example might help respondents to put themselves into the hypothetical position of a patient and relate to such a severe situation.[3] In the further description of the experiment, they are informed about all attributes: co-payments, side effects, probability for 12 month survival and expected introduction of a new cure[4].

[2] For example, the American Cancer Society publishes current funding and investment in research online: *www.cancer.org*.

[3] Because of ethical considerations, it is refrained from interviewing actual cancer patients although this may be the preferred approach. Admittedly, imagining being in such a severe situation might still be kind of a cognitive burden for the respondents. However, as I will argue later, this should not be a major problem for the purpose of this study.

[4] Note, the expected remaining lifetime with first-line treatment is calculated as: $P_{survival} \cdot 12 + (1 - P_{survival}) \cdot 0$, i.e. if the first-line treatment fails, survival time is negligible due to severe lethal complications.

3.3.2 Attributes and Levels

As indicated in the previous section, the DCE features two alternatives, each described by four attributes. *Co-payment for the first-line treatment* is the first attribute. Denoting prices as co-payment allows to remain within an insurance environment but yet set prices which directly affect decision-making. The levels of this attribute are set around the actual direct costs of Erlotinib[5] and come as 0€, 1500€, 3000€and 4500€per month. This cost attribute is useful to obtain willingness to pay values for different attributes and situations.

Table 3.1: Attribute Levels

Attribute	Description	Levels
Co-payment for the First-Line Treatment	The co-payment which is to be paid by the patient on a monthly basis.	◊ 0€ ◊ 1500€ ◊ 3000€ ◊ 4500€
Side Effects of the First-Line Treatment	Side effects induced by the first-line treatment.	◊ None: No side effects ◊ Low: Rash; Nausea; Diarrhoea ◊ High: Rash; Nausea; Diarrhoea; Vomiting; Hair Loss; Changes in the Blood Count
Probability for 12 Months Survival/ Remaining Lifetime	The probability to survive 12 months or a safe remaining lifetime.	Safe remaining lifetime: ◊ 6 months safe Probabilities to survive: ◊ 25% for 12 months ◊ 50% for 12 months ◊ 75% for 12 months ◊ 100% for 12 months
Introduction of a new Follow-Up Therapy	The expected time span until the new follow-up therapy will be introduced.	◊ 3 months ◊ 6 months ◊ 9 months ◊ 12 months

[5]Erlotinib is an agent which is used in treating non-small cell lung cancer and which has been authorized for the first-line treatment of patients suffering from advanced or metastatic non-small cell lung cancer by the Committee for Medicinal Products for Human Use European Medicines Agency (2011).

When it comes to treatment choice, it seems reasonable to pay attention to possible *side effects*. The trade-off between quality and quantity of life is believed to be of major importance. Hence, side effects are assumed to have an important influence when deciding for end-of-life treatments and as such enter as second attribute. The attribute is described by three levels, i.e. none, low and high. Each of the levels is explained to respondents in detail. To get a useful interpretation of this attribute, I base this description on actual side effects observed for Erlotinib. This helps to get as close to a real decision situation as possible.
The third attribute is *Probability for 12 months survival/Remaining life time*. This attribute allows analyzing risk preferences ceteris paribus. By confronting the subjects with the decision to (1) choose a safe remaining life time or (2) a chance to live for a specified and longer period but also being exposed to the risk of sudden death, one can draw conclusions about their risk preferences with respect to remaining lifetime. The attribute is determined to have four equidistant levels and one safe remaining lifetime which serves as reference category: 25%, 50%, 75% and 100% for living 12 months and 6 months safe. Both, equidistance and 25% steps, help to ensure a clear understanding of the probabilities and to avoid the possible overweighting of small probabilities when assessing this attribute.
The fourth attribute introduces the option value. It is labeled *Introduction of a New Follow-Up Therapy* and describes the expected duration until a new cure may be ready for the market. There is no further information about the effectiveness of the cure. It comes in four equidistant levels, i.e. 3, 6, 9 and 12 months. The levels of the attributes are described in table 3.1.
All levels vary for *first-line treatment*. The alternative *no treatment* can be interpreted as a kind of opt out choice as there are neither co-payments nor side effects. Also the level of *Probability for 12 months survival/Remaining Lifetime* is chosen to be fixed at 6 months safe. As this attribute-level serves as reference category it allows a clear interpretation of part-worth utilities of the offered treatments with different survival distributions relative to the threshold at 6 months remaining lifetime. It is crucial to model such a clear cutting point, as it not only allows interpreting part-worth utilities relative to this margin but also using it when calculating willingness to pay (WTP) for certain situations to make a statement about risk preferences and the option value: An introduction of a new therapy later than six months from now can only be reached by choosing the first-line treatment, which entails the risk of immediate death. Hence, at equal objective expected values, choosing the risky first-line treatment unveils risk-loving behavior. The introduction of a new follow-up therapy enters alternative-specific and varies along the choice sets for both alternatives as it does not depend on whether a single patient

chooses first-line treatment or not. As I investigate the effect of the option value, I refrain from interpreting coefficients for side effects, which rather reflect the trade-off between quantity and quality of life. That is I calculate WTPs while fixing side effects, to obtain comparable situations across both alternatives.[6]

3.3.3 Presentation of Choice Sets

Table 3.2: Choice Sets

	First-Line Treatment	**No Treatment**
Co-Payment for the First-line Treatment	1500€/month	0€/month
Side effects of the First-line Treatment	Low	None
Probability to Survive / Remaining Lifetime	75% for 12 months 25% for 0 months	6 months safe
Introduction of a new Follow-up Therapy	9 months	12 months
I prefer:		

I use a fractional factorial design consisting of 25 choice sets. Three rationality tests are included to identify irrational answers. For this purpose I construct choice sets which are composed of arbitrarily set levels. The crucial feature of non-satiation rationality tests is that they include one dominant alternative (Miguel et al., 2005). To improve the questionnaire and to get information about the usability of the procedure, I test a pen and paper version of the DCE with 65 students in bachelor and master programs at the University of Duisburg-Essen. The questionnaire starts by introducing the purpose of the experiment followed by a detailed description of the hypothetical decision situation and the explanation of the attributes and their levels. Furthermore, subjects are informed that there is the option to see the instructions again at any point of the experiment. Table 3.2 shows a typical choice set.

3.3.4 Data Collection and Sample

I cooperate with a German market research institute which provides access to a representative online panel. The estimation sample is created via quota sampling

[6]Obviously, side effects play a crucial role in treatment decisions. I will come back to this aspect later.

to be representative of the German population with respect to age, sex, state of residence and education. The respondents are invited by e-mail and receive a link to the questionnaire. All participants are incentivized by an internal rewarding system in which they earn points which are to be redeemed in the institute's online shop. The reward is paid only in case that the respondents pass all rationality tests to ensure that the results are valid and not just the product of random clicks.

Table 3.3: Descriptive Statistics

	$N(sample)$	$\%(sample)$	$\%(Germ.pop.^{*})$	$\Delta\%$
Sex				
Female	106	51.0	51.0	−0.09
Residency				
Baden-Wurttemberg	22	10.6	13.2	2.6
Bavaria	34	16.3	15.3	−1.0
Berlin	8	3.9	4.2	0.3
Brandenburg	6	2.9	3.1	0.2
Bremen	2	1.0	0.8	−0.2
Hamburg	6	2.9	2.2	−0.7
Hesse	15	7.2	7.4	0.2
Mecklenburg-Western Pomerania	6	2.9	2.00	−0.9
Lower Saxony	20	9.6	9.7	0.1
Northrhine-Westphalia	43	20.7	21.8	1.1
Rhineland-Palatinate	12	5.8	4.9	−0.9
Saarland	2	1.0	1.2	0.2
Saxony	13	6.3	5.1	−1.2
Saxony-Anhalt	6	2.9	2.9	−0.0
Schleswig Holstein	7	3.4	3.5	0.1
Thuringia	6	2.9	2.7	−0.2
Age				
<18	0	0.0	16.3	16.3
18-39	71	34.1	26.3	−7.8
40-59	75	36.1	31.1	−5.0
≥ 60	62	29.8	26.3	−3.5
Education				
Still in School	3	1.4	3.8	2.4
Cert. of Secondary Education	64	30.8	36.3	5.5
Gen. Cert. of Sec. Education	68	32.7	28.8	−3.9
Gen. Qual. for Univ. Entrance	62	29.8	26.6	−3.2
No School Leaving Certificate	1	0.5	3.8	3.3
Not Specified	10	4.8	0.2	−4.6

*Own calculations based on data from the German Federal Statistical Office (Statistisches Bundesamt, 2012)

Overall 495 individuals are invited in several waves to improve representativity with respect to age, gender, education and residency in Germany. 260 respondents fully answered the questionnaire, leading to a response rate of 53%. As indicated above, those respondents who do not pass all three rationality tests are

excluded from further analysis, as I assume that they do not answer wholeheartedly or might have lost concentration.[7] In this sample, that means dropping data of 52 individuals or exactly 20%. In total, 208 individuals are included in the analysis yielding 10,400 (208·(28-3)·2=10400) observations for the first specification, as each of the 25 choice sets consists of two distinct alternatives.
The questionnaire features 4 parts: The introduction, the 28 choice sets, a lottery approach to identify risk preferences and some socio-economic questions. The introduction explains the purpose of the experiment, the hypothetical framing and the attributes as well as the choice task itself. The information given in the introduction is accessible for the complete duration of the experiment. The Lottery approach draws upon the standard Holt and Laury (2002) procedure. It is modified to fit the framing in that respondents choose between lotteries with varying survival distributions instead of monetary values. By determining a switching point between a lottery with low variance and a lottery with high variance in survival time, I can state the risk preference with respect to remaining life time. This determination of risk preference types can then be used to identify subgroups to intensify the analysis of heterogeneity in the DCE.
Table 3.3 shows descriptive statistics of the final sample. The sample is found to be close to the composition of the German population in the four characteristics that are used for its construction. While there is no difference for gender and negligible difference for residency, there is some slight overrepresentation of general certificates of secondary education and general qualification for university entrance going along with slight underrepresentation of no school leaving certificates and certificates of secondary education. Further, the market research institute's panel does not include persons below 18 years of age. Hence, the sample exhibits a deviation of sample shares from population shares in each of the age groups.
A further important aspect that should be addressed before starting the analysis of the data is the respondents' understanding of the task illustrated in table 3.4. Respondents are asked whether they found it hard to understand the task and if it was difficult to take a decision in the particular choice situations. A large majority of 79% finds the task easy and very easy to understand. Only about 3% find it very hard. Concerning the difficulties to take decisions gives a slightly different picture. More than 50% find it hard or very hard to make decisions in the specific choice sets. This might be due to two main reasons. Firstly, the hypothetical situation could have been a cognitive burden for some of the subjects. Secondly, the attributes are chosen to be of high relevance for the situation. Hence, difficulties in

[7] As Lancsar and Louviere (2006) point out, ignoring respondents who failed rationality tests might not be appropriate. In my analysis, including those who failed rationality tests does not change mean coefficients qualitatively.

decision-making could be attributed to the demanding task to trade off different important attributes. Such difficulties in decision-making are intended to obtain useful trade-off results.

Table 3.4: Understanding of Tasks and Decision Scenarios

	Percentage
Difficulties Understanding the Task	
Not Hard at All	21.15
Not Very Hard	57.69
Hard	18.27
Very Hard	2.88
Difficulties Making Decisions	
Not Hard at All	3.85
Not Very Hard	43.27
Hard	45.67
Very Hard	7.21

Own calculations. N=208.

3.3.5 Data Analysis

The analysis is performed by estimating mixed logit models using the Stata routine mixlogit (Hole, 2007b). The dependent variable is a binary choice indicator, which becomes 1 if an alternative is chosen. As base levels low side effects, a life expectancy of 6 months safe and expected introduction of a new therapy in 6 months time are used. The co-payment attribute enters as the only non-random parameter and with its respective EUR values. I estimate part-worth utilities for each attribute level which enter the two distinct indirect utility functions for my preferred specification.

$$\begin{aligned}
V_{in} &= \beta_{0in}(Constant) \\
&+ \beta_1 Co - Payment \\
&+ \beta_{2,n} 25\%Survival + \beta_{3,n} 50\%Survival + \beta_{4,n} 75\%Survival + \beta_{5,n} 100\%Survival \\
&+ \beta_{6,n} NoSideEffects + \beta_{7,n} StrongSideEffects \\
&+ \beta_{8,n} T : 3Months_i + \beta_{9,n} T : 9Months_i + \beta_{10,n} T : 12Months_i
\end{aligned}$$

$$
\begin{aligned}
V_{jn} &= \beta_1 Co - Payment \\
&+ \beta_{6,n} NoSideEffects \\
&+ \beta_{11,n} N: 3Months_j + \beta_{12,n} N: 9Months_j + \beta_{13,n} N: 12Months_j \\
With: & \\
V_{in} &= \text{First-Line Treatment} \\
V_{jn} &= \text{No Treatment}
\end{aligned}
$$

V_{in} describes the utility function of *first-line treatment*, while V_{jn} indicates the respective utility function of *no treatment*. To avoid problems concerning the interpretation of the constant term when using dummy coding, effects coding is applied for all levels. That ensures a meaningful interpretation of the constant as the effects of the levels are not confounded with the intercept. Thus the alternative specific constant in V_{in} captures all unobserved sources of utility associated with this alternative (Bech and Gyrd-Hansen, 2005). As the co-payment attribute enters the analysis with its EUR value, I can calculate the marginal rate of substitution between the attributes and co-payment, which reflects the willingness to pay for an attribute. In principle, the part worth utilities can be used to calculate utility values for all possible situations by adding up the corresponding coefficients directly. Based on those values, different situations can be compared and one can draw conclusions about choice behavior and risk preferences. As it is more convenient to interpret, I use WTPs that reflect individual preferences in the analysis of the option value.

3.4 Results

Ceteris Paribus Interpretation of Part-worth Utilities

Table 3.5 shows the results of the mixed logit estimation including all main effects for the pooled sample. All coefficients in this model are highly significant except for survival probability of 50% which is significant at 5% and the alternative specific constant which is not found to be statistically significant. The coefficients show the expected signs, i.e. less side effects are preferred over more side effects and higher chances of 12 months survival are preferred over smaller probabilities. Further, a shorter expected time until introduction of a new cure is associated with a higher part-worth utility than a longer expected time and higher costs are less

Table 3.5: Mixed Logit Estimation - Pooled Sample

	Pooled	
Mean		
Co-Payment	-0.710^{***}	(0.052)
Constant	0.163	(0.124)
No Side Effects	0.317^{***}	(0.054)
Strong Side Effects	-0.600^{***}	(0.070)
25% survival	-1.128^{***}	(0.108)
50% survival	-0.176^{**}	(0.075)
75% survival	0.262^{***}	(0.086)
100% survival	1.289^{***}	(0.098)
T: 3 months	0.570^{***}	(0.080)
T: 9 months	-0.285^{***}	(0.089)
T: 12 months	-0.579^{***}	(0.102)
N: 3 months	1.375^{***}	(0.118)
N: 9 months	-0.840^{***}	(0.099)
N: 12 months	-1.350^{***}	(0.091)
Standard Deviation		
Constant	0.852^{***}	(0.130)
No Side Effects	0.038	(0.030)
Strong Side Effects	0.015	(0.063)
25% survival	0.495^{***}	(0.115)
50% survival	0.308^{***}	(0.094)
75% survival	0.526^{***}	(0.128)
100% survival	0.176	(0.146)
T: 3 months	0.029	(0.028)
T: 9 months	0.023	(0.051)
T: 12 months	0.057	(0.060)
N: 3 months	0.525^{***}	(0.100)
N: 9 months	0.389^{**}	(0.187)
N: 12 months	0.500^{***}	(0.171)
N	10,400	
LR_{χ^2}	696.54^{***}	

Note: Mixed logit estimation. Standard errors (clustered on individual level) in parentheses. *** p<0.01; ** p<0.05; * p<0.1

valued. While these results are not surprising in itself, the crucial aspect for the evaluation of risk preferences is captured in the attribute *50% Survival*. This attribute estimates the part-worth utility of a 12 months survival probability of 50% relative to the base category 6 months safe. As the expected remaining lifetime is identical for both attributes, a negative coefficient exhibits risk-aversion, ceteris paribus. The coefficient in the pooled mixed logit regression is negative and significant, indicating that respondents prefer certainty about the remaining lifetime compared to a lottery with the same expected value, i.e. they can be seen as being risk-averse in the mean. However, there seems to be a considerable amount of heterogeneity in the sample as can be found from the nonzero and significant estimate for the standard deviation. As the mixed logit model estimates the complete distribution, it allows us to analyze heterogeneity in more detail. Therefore, I calculate the percentage of the sample that would exhibit risk-loving behavior by relating the estimated standard deviation to the estimated mean with $1 - \Phi(-\hat{\beta}_k/\hat{\sigma}_k)$. Roughly 28% of the sample rather prefer the lottery over the safe remaining lifetime.

To analyze the preference heterogeneity in more detail, I combine the DCE

Table 3.6: Mixed Logit Estimation - Subsamples

	Risk-Averse		Risk-Loving	
Mean				
Co-Payment	-0.693^{***}	(0.067)	-0.741^{***}	(0.079)
Constant	-0.002	(0.186)	0.349^{**}	(0.157)
No Side Effects	0.359^{***}	(0.080)	0.302^{***}	(0.076)
Strong Side Effects	-0.617^{***}	(0.104)	-0.613^{***}	(0.103)
25% Survival	-1.262^{***}	(0.184)	-1.027^{***}	(0.144)
50% Survival	-0.234^{**}	(0.110)	-0.099	(0.102)
75% Survival	0.209^{*}	(0.125)	0.262^{**}	(0.121)
100% Survival	1.343^{***}	(0.148)	1.248^{***}	(0.144)
T: 3 Months	0.703^{***}	(0.111)	0.452^{***}	(0.111)
T: 9 Months	-0.461^{***}	(0.132)	-0.160	(0.127)
T: 12 Months	-0.604^{***}	(0.154)	-0.547^{***}	(0.133)
N: 3 Months	1.600^{***}	(0.156)	1.192^{***}	(0.181)
N: 9 Months	-0.972^{***}	(0.129)	-0.696^{***}	(0.148)
N: 12 Months	-1.566^{***}	(0.136)	-1.166^{***}	(0.113)
Standard Deviation				
Constant	0.811^{***}	(0.184)	0.728^{***}	(0.108)
No Side Effects	0.009	(0.041)	0.043	(0.055)
Strong Side Effects	0.083	(0.124)	0.142	(0.173)
25% Survival	0.581^{**}	(0.291)	0.387^{***}	(0.140)
50% Survival	0.118	(0.356)	0.256^{***}	(0.096)
75% Survival	0.705^{***}	(0.178)	0.462^{***}	(0.121)
100% Survival	0.031	(0.105)	0.400^{***}	(0.151)
T: 3 Months	0.023	(0.044)	0.043	(0.043)
T: 9 Months	0.030	(0.051)	0.019	(0.063)
T: 12 Months	0.028	(0.084)	0.013	(0.095)
N: 3 Months	0.512^{***}	(0.180)	0.515^{***}	(0.176)
N: 9 Months	0.250	(0.206)	0.525^{*}	(0.279)
N: 12 Months	0.580^{***}	(0.175)	0.234	(0.402)
N	5,500		4,900	
LR_{χ^2}	470.61^{***}		302.72^{***}	

Note: Mixed logit estimation. Maximum simulated likelihood. Standard errors (clustered on individual level) in parentheses. *** p<0.01; ** p<0.05; * p<0.1

with the lottery choice approach to perform a subgroup analysis as presented in table 3.6. The subgroups are formed based on results from the Holt and Laury (2002)-type approach. Therefore, the pooled sample is split into those who were identified as risk-averse and those who showed risk-loving behavior in the lottery choice approach.

For the subsample of identified risk-averse persons in column 1, the point estimate on 50% Survival increases in absolute size indicating a stronger preference for the safe remaining lifetime. Further, the significant heterogeneity around the mean of 50% Survival disappears. Column 2 presents the results for the corresponding subsample of identified risk loving persons. The coefficient for 50% Survival is not statistically different from zero. Note, as one rather expects a positive point esti-

Table 3.7: Interaction Model - Subsample: Risk-Loving

	Interaction Model	
Mean		
Interaction: Exp. · Cons.	-0.186^{*}	(0.113)
Co-Payment	-0.740^{***}	(0.079)
Constant	0.331^{**}	(0.160)
No Side Effects	0.303^{***}	(0.075)
Strong Side Effects	-0.609^{***}	(0.101)
25% Survival	-1.023^{***}	(0.141)
50% Survival	-0.100	(0.102)
75% Survival	0.260^{**}	(0.122)
100% Survival	1.247^{***}	(0.144)
T: 3 Months	0.454^{***}	(0.111)
T: 9 Months	-0.156	(0.127)
T: 12 Months	-0.552^{***}	(0.133)
N: 3 Months	1.188^{***}	(0.181)
N: 9 Months	-0.694^{***}	(0.148)
N: 12 Months	-1.165^{***}	(0.113)
Standard Deviation		
Constant	0.736^{***}	(0.129)
No Side Effects	0.047	(0.045)
Strong Side Effects	0.151	(0.144)
25% Survival	0.352^{***}	(0.128)
50% Survival	0.273^{***}	(0.095)
75% Survival	0.464^{***}	(0.130)
100% Survival	0.370^{**}	(0.156)
T: 3 Months	0.043	(0.043)
T: 9 Months	0.024	(0.067)
T: 12 Months	0.021	(0.059)
N: 3 Months	0.515^{***}	(0.180)
N: 9 Months	0.499^{*}	(0.293)
N: 12 Months	0.270	(0.343)
N	4,900	
LR_{χ^2}	311.86^{***}	

Note: Mixed logit estimation. Maximum simulated likelihood.
Standard errors (clustered on individual level) in parentheses.
*** p<0.01; ** p<0.05; * p<0.1

mate, there might be a considerable misclassification error, which can also be seen from the estimated standard deviation. Apparently, the identification of risk preferences by the lottery approach does not perfectly coincide with the DCE. Some of those identified as risk averse by the DCE might actually end up as risk-loving in the Holt and Laury (2002)-approach. Probably, different degrees in the complexity of tasks of lottery choices and DCE decisions lead to different classifications of individuals.[8] This might be the reason that I do not find a positive coefficient for 50% Survival in the risk-loving sample. However, in contrast to the risk-averse sample, the risk-loving subsample obtains some utility of the risky first-line treatment from unobserved sources as can be seen from the positive and significant coefficient for the alternative-specific constant. To further explore this finding, I interact the constant with a binary indicator which becomes one if the respondent has experiences with cancer in her closer family.[9] I find a significantly negative coefficient for this interaction effect. Hence, based on unobserved sources of utility, persons in the risk-loving subsample prefer first-line treatment less if they have experiences with cancer in their closer family.

A Willingness to Pay Interpretation – Introducing the Option Value

Departing from the ceteris paribus analysis conducted so far, I proceed by calculating willingness to pay estimates for different situations to analyze the effect of the option value. This allows a more intuitive interpretation of comprehensive situations. As the discrete choice model is linear in parameters, the willingness to pay estimates are obtained by calculating the marginal rate of substitution between an attribute and the cost attribute, which is measured in monetary units, i.e. $\widehat{WTP_i} = \hat{\beta}_i/\hat{\beta}_{co-payment}$. To obtain confidence intervals, I calculate the willingness to pay estimates using stata's wtp-plugin (Hole, 2007a). I again start by interpreting the results for the pooled sample. To evaluate the influence of the option value with respect to risk preferences, I calculate the willingness to pay for situations with identical expected outcomes in remaining lifetime. That is, the general situation includes an expected remaining lifetime of 6 months and no side effects. I then calculate the willingness to pay including the option value for two situations in which the expected introduction of a new cure crosses the threshold of the expected remaining lifetime, disregarding the quality of life. The results are shown in Table 3.9. For the situation in which a new cure is expected to be approved within 3 months from now, one sees that the willingness to pay for not taking part in a treatment exceeds the willingness to pay for treatment. That is, individuals prefer the non-risky alternative if they expect a new cure to evolve within their safe remaining lifetime. This is very much in line with findings from the ceteris paribus analysis.

[8] I also have data on the standard approach (Holt and Laury, 2002) using monetary values. Results are qualitatively identical when applying this approach. Hence, I stick to the initial measure.

[9] As I suspected experiences to probably influence decision making in the setting, this variable was obtained by the socioeconomic questionnaire.

Table 3.8: Willingness To Pay

	Pooled	Risk-Averse	Risk-Loving
Constant	229.27	−2.29	470.76**
No Side Effects	445.84**	518.27**	407.81**
Strong Side Effects	−844.52**	−890.16**	−827.19**
25% survival	−1589.33**	−1821.39**	−1386.46**
50% survival	−247.42**	−337.81**	−133.60
75% survival	369.55**	302.35	353.62**
100% survival	1815.54**	1939.01**	1684.93**
T: 3 months	802.53**	1014.81**	609.93**
T: 9 months	−401.83**	−666.10**	−216.02
T: 12 months	−815.78**	−871.76**	−738.71**
N: 3 months	1936.41**	2310.14**	1609.66**
N: 9 months	−1182.96**	−1402.71**	−939.31**
N: 12 months	−1901.99**	−2260.83**	−1574.08**

WTP-estimates and confidence intervals obtained by the stata wtp-plugin (Hole, 2007a). All estimates multiplied by 1000 as attribute levels entered in 1000EUR. ** p<0.05.

Introducing an option value of today's first-line treatment shifts the preferences. Individuals prefer risky treatments in case they offer the chance of living to see a new cure even if benefits are uncertain. One can infer this result from the higher willingness to pay for treatment, if the new therapy is expected to be approved beyond the threshold of 6 months. Individuals prefer accepting the high risk of immediate death if they thereby obtain the chance to take part in a future therapy, which success is unknown. That is, a higher preference for *first-line treatments* in presence of the option value exists. As already indicated, the quality of

Table 3.9: WTP – Values for Specific Situations

Expected introduction of a new therapy:	First-line treatment	No treatment
3 months	1230.24	2382.25
9 months	25.86	-737.12

WTP for a situation with an expected remaining life time of 6 months and no side effects. Preferred options are shaded in gray.

life after treatment may play a decisive role in treatment choice. One can see from the results that strong side effects have a large negative influence on the overall utility. The results hold as long as no strong side effects are involved. Strong side effects of treatments may overcompensate the effect of the option value leading to a preference for *no treatment*. However, as I am interested in isolating the effect

Table 3.10: WTP – Values for Specific Situations - Subsample: Risk-averse

Expected introduction of a new therapy:	First-line treatment	No treatment
3 months	1192.98	2828.41
9 months	-487.93	-884.44

WTP for a situation with an expected remaining life time of 6 months and no side effects.
Preferred options are shaded in gray.

of the option value on choice behavior, I refrain from interpreting the trade-off between quality and quantity of life. Including this trade off into the analysis would affect the comparability of alternatives. I acknowledge the importance of side effects for treatment choice, which was the initial reason for incorporating it into the experiment.

In order to analyze the heterogeneity in the sample in more detail, I perform the same analysis for the risk-averse subsample. Results indicate, that even those individuals identified as being risk-averse by the lottery approach tend to accept the risk of the first-line treatment in presence of the option value. Even though they have a stronger preference for the safe remaining lifetime ceteris paribus, they accept taking the risk of immediate death if the option value is involved. That is, results for the pooled sample are not driven by extreme risk-loving behavior of a minority.

3.5 Conclusion

This study uses a DCE to analyse treatment choice behavior in end-of-life situations. The DCE features two mutually exclusive alternatives of treatment choices which vary in their survival probabilities. As individuals are forced to decide for one of the two provided alternatives, the DCE induces respondents to focus on the opportunity costs of the alternatives which produces reasonable trade-off results. I first elicit the part-worth utilities of the attributes by applying a mixed logit model. Interpretation of the coefficients yields risk-aversion with respect to remaining life time. Afterwards, I extend the analysis by introducing an option value and calculating the mean willingness to pay for different situations. The analysis identifies an influence of the option value of future therapies with unknown outcomes, which leads one to predict risky treatment choices. Hence, results suggest, that the option value induces patients to choose risky, marginally effective treatments. An option value can come up from many sources, be it by remarks of health care personnel, seeing a drug entering the final stage of approval, media reports or simply just rumors. All these sources may evolve some option value - or less technically speaking – raise hope. This hope is likely to be subjectively overwheighted and rises risk acceptance with respect to remaining life time. Additionally, insurance cushions the financial consequences of treatment for patients, which potentially increases demand even further. We therefore see terminally ill patients applying for chemotherapies which promise only a marginal prolongation of life. As an aside, apart from terminal situations a similar motive might explain the trend towards using alternative treatments which do not meet the requirements of evidence-based medicine. Many social insurances in Germany recently started covering costs for alternative treatments such as acupuncture, homeopathy or osteopathy to meet the demand. Many of those treatments are not only offered to treat minor ailments but also severe diseases. Overall, this suggests that personal perceptions about the chance of being cured play a major role in patients' treatment demand.

Overweighting of small probabilities apparently plays a crucial role when it comes to terminally ill patients. There probably exists a gap between subjective perception of probabilities and objective chances of being cured. Prospect theory approaches this phenomenon explicitly and predicts risk-loving behavior in the domain of losses (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Whether individuals evaluate outcomes as gains or as losses depends on their individual reference point. As this study obtains results from a representative German sample, the average reference point is likely not to coincide with that from terminally ill patients as diagnosis and suffering from a disease probably shifts the reference point. However, Rasiel et al. (2005) point out that the reference point might change slowly, which explains risk-loving choices of terminally ill patients. There is an ongoing debate about whose utility to measure when evaluating health care measures (Ubel et al., 2000). It has been argued, that the general public should be the focal point, as it is the society's resources that are allocated among diseases (Gold et al., 1996; Brazier, 2008). It is hence useful to analyze hypothetical preferences, acknowledging the possible lack of external validity with respect to the group of actual patients. However, financing decisions in social insurances are typically not made by patients but by (usually) more healthy policymakers, which could only put themselves in the hypothetical situation of a patient. This will presumably not shift their actual reference point downwards.

The high demand for marginally effective treatments negatively affects the financial state of the insurers and withdraws resources from other treatments (Baily, 2011). However, marginally effective treatments in terminal situations might have a higher utility than can be measured directly by valuation of medical indicators of the treatment itself. The hope for new therapies adds an additional value to terminal care that is important to individuals and even leads to risky treatment choice behavior. This hope is neglected in cost utility-assessment of treatments, that explicitly focuses on the trade-off between quality and quantity of life. Even though marginally effective treatments are widely discussed as possibly offering opportunities to posteriorize or ration treatments, policy-makers should keep in mind that the underlying utility of marginally effective treatments may be high. That is, although many terminal care measures are only marginally effective the option value needs to be acknowledged when conducting cost-utility analysis to evaluate treatments.

4 Fear of Unemployment and its Effect on the Mental Health of Spouses

4.1 Introduction

Losing one's job is connected to numerous negative consequences. Besides the obvious economic cut due to the loss of income[1], previous economic research has shown that unemployment influences individuals' long-term labor market prospects (Clark et al., 2001; Knabe and Rätzel, 2011). Besides these economic losses, there are other fields of life affected as well. Among these non-monetary consequences is a loss in life satisfaction (Winkelmann and Winkelmann, 1998; Kassenböhmer and Haisken-DeNew, 2009) or even an influence on suicide probability (Ruhm, 2000). A central aspect of the research on non-monetary consequences of job loss are health effects. While some authors have found adverse mental health effects on the unemployed (Korpi, 1997; Björklund and Eriksson, 1998; Green, 2011), others have not found these effects (e.g. Browning et al., 2006; Böckerman and Ilmakunnas, 2009; Salm, 2009; Schmitz, 2011).

The vast majority of studies on the consequences of job loss are concerned with the treated individuals themselves. While there may be already severe negative effects on unemployed individuals, the total effect is even larger as not only the unemployed themselves are affected but also their families and spouses (Winkelmann and Winkelmann, 1995; Siedler, 2011; Kind and Haisken-DeNew, 2012; Marcus, 2013). Financial losses are not only borne by individuals but all household members. Considering monetary effects on the unemployed and their families might

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[1]Transfer payments, e.g. unemployment benefits, partly offset the financial loss in many countries. However, while the generosity of benefit schemes varies substantially between countries, a full compensation of previous earnings is hardly to be found, hence, financial losses are a sure consequence of an unemployment spell.

still not cover the devastating effect of unemployment to the full extent. Non-monetary consequences can also be expected to spill over to families and spouses. Besides the monetary and non-monetary effects of actual job loss on the unemployed as well as their families, there is one more channel to be considered.
Not only the event of unemployment but also the fear of unemployment can be expected to have negative effects. Job security[2] is one of the central aspects of satisfaction with a job (Knabe and Rätzel, 2010; Geishecker, 2009) and the fear of unemployment has been shown to decrease mental health of individuals significantly (Burgard et al., 2009; Reichert and Tauchmann, 2011; Caroli and Godard, 2013).
Against the background of previous findings, this paper analyzes the impact of the fear of unemployment on the mental health of spouses.[3] Like the actual event of unemployment, the fear of job loss can affect partners over different channels. Firstly, there is an expected financial cut. While previous research has shown that the non-monetary effects of unemployment are at least as important as the monetary ones for treated individuals, the driving force behind the fear of losing one's job are most likely sorrows concerning the financial stability. These sorrows are hardly borne by individuals in insecure jobs alone but also by their spouses – especially, if the main income earner in a household is threatened by unemployment. Secondly, even if the financial situation remains stable, spouses might share their partners' concerns as feeling for a spouse and her sorrows and fears is a central part of (most) relationships. Building on these considerations, we analyze the question whether the fear of unemployment spills over to spouses empirically.
To our best knowledge, this study is the first one to identify spillover effects of job insecurity. Using data from the German Socio-Economic Panel (SOEP), it can be shown that there are considerable spillover effects of insecure job situations on partners. The fear of job loss is a result of actual unemployment – in times of full employment, it would hardly exist. In this light, the analysis shows the the costs of unemployment are even higher than previously assumed. Furthermore, while perfectly disentangling the channels over which individuals suffer from their spouses' job insecurity is hardly possible, there is some indication that it is not only financial fear but individuals also feel with their partners' worries.
The paper is structured as follows: The empirical strategy is explained in Section 4.2, in Section 4.3, the data source is introduced and descriptive statistics of the sample are presented and discussed. Results are presented and discussed in Section 4.4. A conclusion can be found in Section 4.5.

[2]The terms job (in)security and fear of unemployment are used interchangeably in this paper.
[3]The terms spouse and partner are used interchangeably in this paper as all couples cohabit and more than 80% are married.

4.2 Empirical Strategy

The research question is whether individuals' perceived job insecurity has effects on the mental health of their partners. Hence, the dependent variable of our empirical model is the Mental Component Summary Scale (MCS), which is reported on a 0 - 100 scale and can be interpreted linearly. Due to the nature of the outcome variable, we apply linear regression methods. More precisely, we set up the following equation and apply OLS techniques:

$$MCS_{it}^{1} = FearUE_{it}^{1}\eta + FearUE_{it}^{2}\beta + X_{it}^{1}\zeta + X_{it}^{2}\gamma + H_{it}\delta + \theta_t + \varepsilon_{it} \tag{4.1}$$

Individuals and periods are indicated by the subscripts i and t, respectively, the superscripts 1 and 2 relate to partner 1 and partner 2, respectively. For each couple, we observe both partners. Partner 1 is always the outcome partner, the partner whose MCS is explained. Partner 2 is the treatment partner, hence, the one whose perceived job insecurity appears as right-hand side variable. The coefficient of main interest is β, the spillover effect of fear of unemployment of partner 2 on their spouse's mental health. However, partner 1's own fear of job loss is also included because not accounting for it might results in an omitted variable bias – as Reichert and Tauchmann (2011) show that the MCS is heavily affected by own job insecurity. The vectors X_{it}^{1} and X_{it}^{2} contain socio-economic characteristics of both partners. In addition, X_{it}^{2} includes a set of job characteristics of partner 2. H_{it} is a vector of household characteristics that refer to both partners, and θ_t includes a full set of calendar time dummies. ε_{it} represents the regression error term. To account for correlations between observations of both partners, all models are estimated using standard errors that are clustered at the household level and allow for arbitrary intra-cluster correlations.

$$MCS_{it}^{1} = FearUE_{it}^{1}\eta + FearUE_{it}^{2}\beta + X_{it}^{1}\zeta + X_{it}^{2}\gamma + H_{it}\delta + \theta_t + \alpha_i^{1} + \varepsilon_{it} \tag{4.2}$$

In a second step, we include a full set of individual fixed effects (α_i^1 in Equation 4.2). Introducing fixed effects is an important step towards unbiased estimates for at least two reasons. First, the MCS is a subjective measure of an individual's mental health. As Ferrer-i Carbonell and Frijters (2004) have shown, it is crucial to account for individual fixed effects to get meaningful results from regressions on subjective outcome variables. Second and equally important in the present setting, individual fixed effects control for another potential source of bias: Assortative mating. According to the theory of assortative mating (e.g. Kalmijn, 1994; Pencavel, 1998), couples share some common characteristics such as beliefs and attitudes. Hence, it is quite likely that in rather pessimistic couples, partner 1 scores low on the MCS and their spouse reports rather low job security. Individual fixed effects account for this as only the within-variation of individuals is exploited and time-invariant differences do not account to the effects of explanatory variables. Hence, a common negative attitude within a couple does not bias results as only changes over time are considered. However, it is important to bear in mind that individual fixed effects absorb only correlations that are time-invariant but cannot deal with unobserved shocks that are time-variant.

There might also be concerns that the estimation results are affected by reverse causality as subjective information from both individuals enter the model. To be more precise, it might be conceivable that if partner 1 suffers from mental health problems, this might also induce/ increase her own fear – or the spouse's fear of job loss. Concerning the own fear, it is likely that mental health problems might lead to a more pessimistic evaluation of the own job situation. The intuition behind the idea of reverse causality for the spouse's fear of job loss is less direct. Keeping the job might become more important for partner 2 – at least from a financial perspective – when the partner gets severely ill and might not be able to work (anymore).

To account for reverse causality, Reichert and Tauchmann (2011) use staff reduction at an individual's employer in the previous year as an instrument for subjective job insecurity. However, in their analysis, the focus lies on the effects of fear of unemployment for the affected individual, hence, it might well be the case that more or less healthy individuals sort into more or less secure jobs. In this analysis, the effect of job security of one individual on her spouse is of main interest, hence, it can be argued that in the estimation of β, reverse causality should not play a crucial role.

Nevertheless, it cannot be ruled out entirely for the estimation of β and the estimation of η – the coefficient of the own fear of unemployment – is likely subject to this source of bias. However, to be a valid instrument, staff reduction must be sufficiently correlated with the fear of unemployment and simultaneously fulfill the exclusion restriction. While the former condition is rather unproblematic, the validity assumption might be violated, as we cannot rule out the possibility that potential effects operate also through other channels than the fear of unemployment – e.g. when individual's suffer from the loss of colleagues. As we lack a valid instrument to account for reverse causality, we aim at reducing concerns by estimating a model including a lagged dependent variable.

Finally, having subjective variables both on the left-, as well as on the right-hand side of the equation might be an issue. Therefore, we choose not to use staff re-

duction as an instrument but to exploit staff reduction as an objective measure that directly enters the model as proxy for partner's fear of unemployment. Obviously, fear of unemployment and staff reduction in the company are no perfect substitutes. First, respondents can feel their job to be insecure although there were no layoffs during the last year and, second, they may know their job to be secure although there were layoffs. Still, the two variables are significantly correlated and therefore staff reduction can serve as a proxy for the fear of unemployment to validate the direction of causation.
To sum up, the empirical strategy is conducted in four consecutive steps. First, OLS regressions are applied to show the direction of correlations. To account for the subjective nature of the outcome variable as well as assortative mating, individual fixed effects are controlled for. In the next step, we estimate a model including the lagged dependent variable to reduce concerns about reverse causality and finally, we check the robustness of the findings by using staff reduction as a proxy variable for the subjective fear of unemployment.

4.3 Data

The empirical analysis is based on representative panel data from the German Socio-Economic Panel (SOEP, v.29). The SOEP is a longitudinal German survey and provides comprehensive information on both, individual and household level. More precisely, all household members aged 17 and older are interviewed annually on a wide range of socio-economic characteristics, such as financial, working and health conditions. The SOEP started in 1984 and was subject to several refreshments and enlargements resulting in a current panel of more than 20,000 individuals in 2013 (DIW, 2014).
The estimation sample is restricted to couples for which information on both partners is provided. As the main interest lies on the effect of partner's fear of unemployment, we exclude observations if partner 2 is not employed. Further couple-year observations are excluded if partner 2 is a civil servant because this group is subject to very strict dismissal protection laws in Germany. In addition, we restrict our sample to partners aged 65 and younger, since this is the statutory retirement age in Germany and fear of unemployment usually does not apply beyond this threshold. We end up with a final estimation sample of 27,081 person-year observations from 10,798 individuals.
The dependent variable in all regression models is the Mental Component Summary Scale (MCS), which is frequently used in health economics studies (e.g. Schmitz, 2011; Marcus, 2013) and has been proven to be a good measure of in-

dividual mental health (Gill et al., 2007; Salyers et al., 2000). The MCS is generated from a battery of health-related quality of life indicators, which are part of the SF-12 questionnaire. The SF-12 is a short version of the SF-36 and involves six questions covering different fields of psychological conditions.[4] The MCS ranges from 0 to 100 and was standardized to have a mean of 50 and a standard deviation of 10 in 2004. Higher MCS-values are associated with better mental health conditions (Andersen et al., 2007). As the MCS was first obtained in 2002 and is available biennially, the estimation sample is constructed from the six waves to 2012.

The key explanatory variable in the present analysis is a measure of partner's perceived job insecurity. SOEP participants are asked whether they are *very concerned*, *somewhat concerned*, or *not concerned at all* about their current job situation. Following the work of Reichert and Tauchmann (2011), we collapse the information of the partner's perceived job insecurity into a binary indicator that becomes 1 if the partner reports at least some concerns about his employment status and zero otherwise.[5]

As a robustness check, we use the objective measure *staff reduction* as proxy for the subjective fear of unemployment. It takes the value 1 if the employer laid off workers in the preceding year and zero otherwise.

The set of control variables can be categorized into three groups: Socio-economic controls, partner-controls and household-controls. Socio-economic controls contain the variables employment status, age, years of education and gross labor income. Partner controls comprise age, years of education and gross labor income. Beyond that, we let information on partner's fulltime employment history and tenure enter the set of partner controls. Household controls account for variables that affect both partners and include an indicator for children living in the household, household size as well as an indicator of residency in East or West Germany. In addition, we control for marital status of the couple, i.e. whether or not the couple is married. Finally, we include a full set of calendar time dummies to control for the overall economic conditions that may affect both perceived job security and mental health. Descriptive statistics of all variables used throughout the analysis are presented in Table 4.1.

There are interesting differences between men and women that are important for interpretation of the results from the subsequent empirical analysis. Given that the respective partner is employed, women are far less likely to be employed than

[4] The remaining six questions refer to physical health conditions.

[5] As a robustness check, we do not collapse the variable into a binary regressor but let *very concerned* and *somewhat concerned* enter the regression. Results are qualitatively unchanged, see Table A4.7.

Table 4.1: Descriptive Statistics

	All			Female			Male		
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.
Mental Health (P1)	27,081	50.41	8.99	13,473	49.62	9.20	13,608	51.19	8.70
Fear of UE (P2)	27,081	0.58	0.49	13,473	0.61	0.49	13,608	0.56	0.50
Controls: Partner 1									
Employed Y/N	27,081	1.00	0.00	13,473	1.00	0.00	13,608	1.00	0.00
Age	27,081	44.27	9.14	13,473	42.95	8.91	13,608	45.56	9.18
Education in Years	27,081	12.56	2.59	13,473	12.48	2.45	13,608	12.64	2.71
Gross Income	27,081	2,612.97	2,356.85	13,473	1,751.97	1,520.02	13,608	3465.44	2703.06
Fear of UE	27,081	0.58	0.49	13,473	0.55	0.50	13,608	0.60	0.49
Big Econ. Worries	27,071	0.19	0.42	13,468	0.19	0.40	13,603	0.19	0.40
Some Econ. Worries	27,071	0.57	0.50	13,468	0.58	0.49	13,603	0.55	0.50
Controls: Partner 2									
Age	27,081	44.22	9.06	13,473	45.46	9.00	13,608	43.00	8.96
Education in Years	27,081	12.55	2.58	13,473	12.63	2.71	13,608	12.48	2.45
Gross Income	27,081	2,603.09	2,341.92	13,473	3,456.32	2,681.06	13,608	1758.32	1537.50
Fulltime Exp.	27,081	17.32	10.92	13,473	22.47	9.83	13,608	12.22	9.45
Tenure	27,081	11.21	9.39	13,473	12.56	9.97	13,608	9.88	8.56
Staff Reduction	21,976	0.23	0.42	10,927	0.25	0.43	11,049	0.21	0.41
Controls: Household									
Children in HH Y/N	27,081	0.46	0.50	13,473	0.47	0.50	13,608	0.46	0.50
# Persons in HH	27,081	3.12	1.05	13,473	3.13	1.05	13,608	3.12	1.05
Married Y/N	27,081	0.83	0.37	13,473	0.83	0.37	13,608	0.83	0.37
East Germany	27,081	0.25	0.43	13,473	0.25	0.43	13,608	0.25	0.43

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2006, 2008, 2010 and 2012. P1 and P2 refer to Partner 1 and 2, respectively.

men (76% vs 89%).[6] Mean gross income of women is considerably lower than men's – this is also true when only considering employed individuals. This is an indication that women may depend more on their partners' income than men do. Hence, women might be more affected by their partners' job insecurity. This descriptive difference is in line with the classical male breadwinner model. In this model, men are the sole/ main income earner of a household.[7] This concept is important for labor market analyses in Germany as the country is well-known for a rather weak female labor market participation – especially when considering that the oldest cohorts in our sample are born in the 1930s/1940s.

4.4 Results

Beginning with the estimation results of the model specification as shown in Equation 4.1, this section proceeds by providing results of further specifications including individual fixed effects, the lagged dependent variable and proxy the subjective insecurity by staff reductions in the company.

[6]Note, this finding is based on a sample including non-working spouses and cannot be seen from table 4.1. The sample will be used in later regressions.

[7]For an overview of the development of this theory, see e.g. Lewis (2001).

Table 4.2: MCS Regressions - Baseline OLS

	OLS Pooled	OLS Female	OLS Male
Fear of UE Y/N	-2.873***	-2.715***	-3.031***
	(0.133)	(0.200)	(0.187)
Partner: Fear of UE Y/N	-1.029***	-0.970***	-1.051***
	(0.134)	(0.205)	(0.184)
Female	-1.880***	–	–
	(0.179)		
Fulltime Y/N	-0.832***	-0.862***	-0.760**
	(0.191)	(0.250)	(0.305)
Fulltime Experience	0.039***	0.031*	0.059**
	(0.014)	(0.017)	(0.029)
Tenure	-0.018**	-0.016	-0.022*
	(0.009)	(0.015)	(0.012)
SC	Yes	Yes	Yes
SC Partner	Yes	Yes	Yes
SC Household	Yes	Yes	Yes
Years	Yes	Yes	Yes
N	27081	13473	13608

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.5; * p<0.1. Standard errors (clustered on household-level) in parentheses. Full regression output is presented in Table A4.6.

4.4.1 Main Results

Table 4.2 shows the baseline OLS results for the pooled as well as sex-split estimations.

As can be seen from Column 1, the coefficient estimate of the own fear of unemployment is large and statistically highly significant in the pooled sample. The coefficient for the variable of main interest, partner's fear of unemployment, exhibits the expected negative sign and is highly significant as well, indicating that partner's perceived job insecurity has negative spillover effects on own mental health. Comparing the coefficients of own fear of unemployment and one's partner's fear of unemployment, the latter one is about two thirds smaller. Nevertheless, the coefficient is still considerably large with -1.029, which translates to more than 10% of a standard deviation of the dependent variable. To obtain a more comprehensive understanding of the underlying effects, Table 4.2 also reports the estimation results for the sex-split samples. Columns 2 and 3, respectively, refer to the subsamples of women and men whose spouse suffers from job insecurity.[8]

[8]Same-sex couples are not regarded here as their number is too low for a meaningful analysis in our data.

Table 4.3: Fixed Effects - Controlling for Own Fear of UE

	FE Pooled	FE Female	FE Male
Fear of UE Y/N	-1.145***	-0.965***	-1.351***
	(0.185)	(0.260)	(0.256)
Partner: Fear of UE Y/N	-0.360**	-0.463*	-0.265
	(0.183)	(0.279)	(0.242)
SC	Yes	Yes	Yes
SC Partner	Yes	Yes	Yes
SC Household	Yes	Yes	Yes
Years	Yes	Yes	Yes
N	27081	13473	13608

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.5; * p<0.1. Standard errors (clustered on household-level) in parentheses. Full regression output is presented in Table A4.2.

Comparing the estimated coefficients across both subsamples reveals that in the simple OLS specification, no considerable differences between the subsamples are to be seen. The coefficients for the own fear of unemployment, as well as the partner's fear of unemployment are equally large across the pooled sample, as well as the male and female subsamples.

OLS results are a first indication that individuals are influenced by their partner's job security. Nonetheless, these results can hardly show more than the direction of correlations. To derive unbiased estimates, individual fixed effects are accounted for in the next step.

Table 4.3 shows the results of the fixed effects regressions. As to be expected, the coefficients for both, the own as well as the partner's fear of unemployment become considerably smaller. The point estimates for the own fear of unemployment are about two thirds smaller than in the simple OLS case, for the partner's fear of unemployment, the coefficients are about half the size compared to the previous estimates. For the own fear of unemployment, the point estimate for the female subsample is smaller than for the male subsample (-0.965 and -1.351, respectively). While the difference between the two coefficients is not statistically significant, it is a further indication that the breadwinner model might be of some importance when interpreting the results. As the own fear of unemployment enters the estimation, all individuals considered are employed by definition – otherwise they could not be afraid of losing their jobs. Nevertheless, males might be the main income earners in dual-income households – in our sample, conditioning on being employed, women earn significantly lower wages than men do on average (€ 1752 vs. € 3465). For the partner's fear of unemployment, the point estimates show the

expected pattern between the different subsamples. That is, the effect for women is larger than for men. Although the point estimate for the male subsample is not statistically significant anymore, overall there is still a considerable reaction to the partner's fear of unemployment to be seen.
While the FE specification accounts for possible bias due to assortative mating and the incomparability of subjective health measures between persons, there might still be a problem with reverse causality. Therefore, including the lagged dependent variable in the regressions could help to minimize reverse causality problems (Gupta and Kristensen, 2008). However, including a lagged dependent variable into a fixed effects model may raise issues concerning the consistency of estimates. We therefore exploit the bracketing property of fixed effects and lagged dependent variable models to confirm our results (Angrist and Pischke, 2008). Following this approach, estimates of the lagged dependent variable model and fixed effects model should bound the true effect. This property is particularly helpful if the range between estimates of both models is not large. The results of the OLS model including the lagged dependent variable is shown in table 4.4. The coefficients for partner's fear of unemployment are highly significant and show the identical pattern as in previous models. Though, they are slightly larger. Comparing the estimates to the original coefficients from the fixed effects model in table 4.3 gives a further hint that the negative effect of partner's fear of unemployment on own mental health is reasonable, as the bounding range between both estimates is rather small. Own fear of unemployment still has a large and highly significant

Table 4.4: OLS - Controlling for Lagged Dependent Variable

	OLS Pooled	OLS Female	OLS Male
Fear of UE Y/N	-1.960***	-1.831***	-2.083***
	(0.125)	(0.188)	(0.174)
Partner: Fear of UE Y/N	-0.554***	-0.631***	-0.463***
	(0.124)	(0.190)	(0.172)
MCS_{t-2}	0.478***	0.473***	0.482***
	(0.009)	(0.012)	(0.012)
SC	Yes	Yes	Yes
SC Partner	Yes	Yes	Yes
SC Household	Yes	Yes	Yes
Years	Yes	Yes	Yes
N	18191	9046	9145

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.05; * p<0.1. Standard errors (clustered on household-level) in parentheses. Full regression output is presented in Table A4.3.

coefficient. The main conclusion remains unchanged. Individuals are affected by their partner's fear of unemployment – although not as strong as they are affected by their own fear.

4.4.2 Including Single-Income Households

So far, the analysis has entirely focused on a selected group of households: Dual-income households. As we controlled not only for one's partner's job insecurity but also for the own one, the sample had to consist of dual-earner households by definition. However, there might be concerns related to own fear of unemployment as a relevant confounder. Concentrating on a sample solely consisting of dual-earner households by the inclusion of own job insecurity might not be appropriate to answer our research questions – and especially to disentangle non-monetary from monetary effects for different reasons. As descriptives on income differences between men and women show, it is likely the case that in dual-income households, one household member is the main income earner and the financial situation of this household heavily depends on this person. However, this situation is far more distinct in single-earner households. Therefore, it can well be assumed that not considering these households underestimates the total effect because those households that are most strongly threatened by financial cuts if one member loses her job are not even considered. Therefore, we include single-income households in this part of the analysis.

To do so, own job insecurity cannot be controlled for. However, if an evaluation of own situation is not included in the regression analysis, results are likely subject to an omitted variable bias. We therefore include a different measure in the analysis: A subjective evaluation of the own economic situation. In the SOEP, the sorrows about the own economic situation are evaluated using the same scale used for the evaluation of job insecurity. While it obviously has a different focus than the question for the own job security, it still grabs financial concerns and can therefore prevent an omitted variable bias – and at the same time allows us to include individuals that have no job insecurity as they are not active in the labor market.

Table 4.5 shows the results for the estimations including own economic worries instead of own fear of job loss.

The coefficients are largely in line with the regressions controlling for the own fear of unemployment. For the pooled sample, it is roughly 5 times (10 times) smaller than having some (big) economic worries, but still considerable in size and significant on the 5% level.

The subsample analysis shows, that the point estimate for partners' job insecurity is largest in the female sample, and statistically significant on the 5% level, while it

Table 4.5: Fixed Effects - Controlling for Economic Worries

	FE Pooled	FE Female	FE Male
Partner: Fear of UE Y/N	-0.370**	-0.502**	-0.236
	(0.154)	(0.220)	(0.208)
Big Econ. Worries	-3.413***	-3.099***	-3.793***
	(0.253)	(0.337)	(0.353)
Some Econ. Worries	-1.659***	-1.639***	-1.667***
	(0.172)	(0.241)	(0.236)
SC	Yes	Yes	Yes
SC Partner	Yes	Yes	Yes
SC Household	Yes	Yes	Yes
Years	Yes	Yes	Yes
N	38865	20890	17975

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.5; * p<0.1. Standard errors (clustered on household-level) in parentheses. Full regression output is presented in Table A4.4.

is only half as large in the male sample and insignificant. While the coefficients for males and females cannot be told apart statistically, they give a hint at differences in the perception of spousal worries concerning the labor market.

It does not come as a surprise that the coefficient for spousal job insecurity is by far smaller than the coefficients for own financial worries – financial stability is the basis of individual's way of life. Nonetheless, spouses' worries concerning the labor market play a role even above financial worries. The coefficients of partner's fear of unemployment can mainly be interpreted as an emotional channel. When controlling for worries concerning the own economic situation, fear of financial losses does not have an effect over this channel. It is rather that individuals feel with their partners and their sorrows that has an effect here. A careful attempt to disentangle monetary from non-monetary channels is done by rerunning the regressions neither including the own fear of job loss nor the own economic worries. Results are shown in table A4.6. The coefficients for partner's fear of unemployment sharply increase. While perfectly disentangling monetary and non-monetary channels is hardly possible in this setting, the difference can be carefully interpreted as the fear of monetary losses.

4.4.3 Proxy-Variable Approach

The previous steps of the analysis have shown that results are qualitatively robust over different specifications. Still, there might be a further problem: Subjective information are used as dependent variable as well as independent variable of main

Table 4.6: MCS Regressions - Proxy: Staff Reductions

	FE Pooled	FE Female	FE Male
Partner: Staff Reduction Y/N	-0.279	-0.291	-0.252
	(0.181)	(0.245)	(0.256)
Big Econ. Worries	-3.475***	-3.306***	-3.687***
	(0.300)	(0.404)	(0.411)
Some Econ. Worries	-1.641***	-1.634***	-1.643***
	(0.204)	(0.288)	(0.275)
SC	Yes	Yes	Yes
SC Partner	Yes	Yes	Yes
SC Household	Yes	Yes	Yes
Years	Yes	Yes	Yes
N	32254	17299	14955

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.5; * p<0.1. Standard errors (clustered on household-level) in parentheses. Full regression output is presented in Table A4.5.

interest. The independent variable of main interest – the fear of unemployment of partner 2 – and the dependent variable – the MCS of partner 1 – are taken from two different individual questionnaires. Hence, common source bias is not supposed to be a major concern. Furthermore, using individual fixed effects ensures that only intra-individual differences are exploited and not inter-person differences. Still, we apply a further step in the analysis to make sure that results are not systematically distorted by the subjectivity of information.

As a final robustness check, we use staff reductions in the previous year as a proxy for spousal job insecurity. Obviously, the measures differ from each other: It is well possible that individuals are afraid of losing their jobs although no one was laid off in the previous year and others might be in secure jobs although others lost their jobs in the same company. Still, these two variables are sufficiently correlated to each other.[9]

As table 4.6 shows, using staff reduction as a proxy for subjective job insecurity does not change the direction of results. While the point estimates for staff reduction are slightly smaller than for subjective job insecurity used in previous regressions, the difference is not statistically significant. The point estimates in subsamples are statistically insignificant, however, the signs of the point estimates support the direction of results.

[9]Reichert and Tauchmann (2011) show that staff reductions are a strong instrument for fear of unemployment.

4.5 Conclusion

This paper investigates the influence of the fear of unemployment on the mental health of spouses. In an empirical analysis on data from the German Socio-Economic Panel, it can be shown that fear of unemployment has considerable and statistically significant effects on partners' mental health. Results are robust over different samples and using the objective variable staff reduction as proxy for fear of unemployment. While effects can be found for men whose partner is afraid of losing her job as well as for females, whose partner is afraid of losing his job, there is some indication that effects on the mental health of women are larger. This can be explained by the male breadwinner model, which still plays an important role in Germany, hence, males are the main income earner in the majority of households. Nevertheless, controlling for the own economic worries in addition to the partner's fear of unemployment shows that the male breadwinner model is not the only explanation for stronger effects on female mental health but that women also seem to be more susceptible to non-monetary influences.

All in all, results show a relevant, not yet studied facet of the adverse effects of unemployment. That the negative consequences of unemployment are by far larger than the financial loss – and not only affect the unemployed themselves but also spill over to their families and partners – is well-known in the economic literature. This paper, however, shows that even worries about the future possibility of losing one's job can have negative effects on spouses, which adds another dimension to the unemployment discussion. This means that although a wide range of unemployment consequences has been revealed, the full effect is still underestimated.

This finding is relevant for several reasons. First, and most obvious, it shows serious negative health consequences, even for people who are not directly affected by a negative treatment. To be precise, the effect is an indirect one for two reasons: First, the analyzed treatment is not the loss of the job but only the fear of a possible job loss. Second, it is not only the person afraid of losing their job who is directly affected but also their partner. Furthermore, from a financial point of view, the treatment of mental illnesses is one of the large components of health care costs in Germany. While not any slight loss in mental wellbeing as reported by the MCS will translate in rising health costs, as an overall driver of mental health it will in sum lead to rising health care costs. Then, long-run effects on productivity can be assumed. As results show, the effects of the fear of unemployment on partner's mental health do not only run over the channel of financial worries but also over non-monetary channels.

A further possible channel that is beyond the scope of this analysis is the question in how far children are also affected by the spillover effects shown here. As our results show, not only individuals affected by job insecurity suffer from this but also their partners, it seems likely that their children are not fully detached.

4.6 Appendix

Table A4.1: MCS Regressions - Baseline OLS

	OLS Pooled	OLS Female	OLS Male
Fear of UE Y/N	-2.873***	-2.715***	-3.031***
	(0.133)	(0.200)	(0.187)
Partner: Fear of UE Y/N	-1.029***	-0.970***	-1.051***
	(0.134)	(0.205)	(0.184)
Female	-1.880***	–	–
	(0.179)		
Age	0.007	-0.040	0.037
	(0.018)	(0.029)	(0.035)
Education in Years	-0.009	0.029	-0.015
	(0.035)	(0.060)	(0.052)
Gross Income	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)
Partner: Age	0.005	0.043	-0.042
	(0.019)	(0.039)	(0.027)
Partner: Education in Years	-0.075**	-0.050	-0.093*
	(0.034)	(0.058)	(0.053)
Partner: Gross Income	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)
Fulltime Y/N	-0.832***	-0.862***	-0.760**
	(0.191)	(0.250)	(0.305)
Fulltime Experience	0.039***	0.031*	0.059**
	(0.014)	(0.017)	(0.029)
Tenure	-0.018**	-0.016	-0.022*
	(0.009)	(0.015)	(0.012)
Partner: Fulltime Y/N	0.085	0.899***	-0.174
	(0.189)	(0.344)	(0.228)
Partner: Fulltime Experience	0.019	0.026	0.024
	(0.013)	(0.031)	(0.016)
Partner: Tenure	-0.005	0.002	-0.018
	(0.009)	(0.013)	(0.013)
Children in HH Y/N	-0.286	-0.558**	-0.139
	(0.226)	(0.280)	(0.268)
# Persons in HH	-0.100	-0.058	-0.181
	(0.109)	(0.138)	(0.127)
Couple married Y/N	0.875***	0.914***	0.774**
	(0.252)	(0.313)	(0.305)
East Germany	-0.348	-0.513*	-0.074
	(0.231)	(0.284)	(0.272)
Years	Yes	Yes	Yes
N	27081	13473	13608

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.5; * p<0.1. Standard errors (clustered on household-level) in parentheses.

Table A4.2: Fixed Effects - Controlling for Own Fear of UE

	FE Pooled	FE Female	FE Male
Fear of UE Y/N	-1.145***	-0.965***	-1.351***
	(0.185)	(0.260)	(0.256)
Partner: Fear of UE Y/N	-0.360**	-0.463*	-0.265
	(0.183)	(0.279)	(0.242)
Age	-0.130	-0.279	-0.154
	(0.153)	(0.187)	(0.259)
Education in Years	0.744**	0.360	1.063**
	(0.345)	(0.512)	(0.450)
Gross Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Partner: Age	0.215	0.237	0.106
	(0.147)	(0.247)	(0.211)
Partner: Education in Years	0.093	0.081	0.201
	(0.266)	(0.410)	(0.343)
Partner: Gross Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Fulltime Y/N	-0.781***	-1.014***	-0.370
	(0.267)	(0.348)	(0.440)
Fulltime Experience	-0.106*	-0.100	0.029
	(0.063)	(0.078)	(0.176)
Tenure	-0.045*	-0.062	-0.038
	(0.027)	(0.042)	(0.035)
Partner: Fulltime Y/N	0.047	0.086	-0.001
	(0.253)	(0.463)	(0.313)
Partner: Fulltime Experience	-0.066	0.105	-0.118*
	(0.058)	(0.169)	(0.069)
Partner: Tenure	-0.000	-0.011	0.008
	(0.023)	(0.030)	(0.037)
Children in HH Y/N	0.128	-0.002	0.275
	(0.324)	(0.415)	(0.403)
# Persons in HH	-0.331*	-0.119	-0.565**
	(0.200)	(0.257)	(0.241)
Couple married Y/N	0.436	0.554	0.406
	(0.482)	(0.670)	(0.573)
East Germany	0.498	1.539	-0.412
	(2.095)	(2.400)	(2.576)
Years	Yes	Yes	Yes
N	27081	13473	13608

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** $p<0.01$; ** $p<0.5$; * $p<0.1$. Standard errors (clustered on household-level) in parentheses.

Table A4.3: OLS - Controlling for Lagged Dependent Variable

	OLS Pooled	OLS Female	OLS Male
Fear of UE Y/N	-1.960***	-1.831***	-2.083***
	(0.125)	(0.188)	(0.174)
Partner: Fear of UE Y/N	-0.554***	-0.631***	-0.463***
	(0.124)	(0.190)	(0.172)
Female	-0.957***	–	–
	(0.156)		
MCS_{t-2}	0.478***	0.473***	0.482***
	(0.009)	(0.012)	(0.012)
Age	-0.004	-0.033	0.018
	(0.015)	(0.023)	(0.029)
Education in Years	-0.008	0.039	-0.033
	(0.028)	(0.046)	(0.042)
Gross Income	0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Partner: Age	0.004	0.025	-0.022
	(0.015)	(0.032)	(0.022)
Partner: Education in Years	-0.057**	-0.095**	-0.013
	(0.028)	(0.046)	(0.041)
Partner: Gross Income	0.000**	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
Partner: Fulltime Y/N	-0.024	0.432	-0.123
	(0.176)	(0.330)	(0.213)
Partner: Fulltime Experience	0.008	0.014	0.011
	(0.011)	(0.025)	(0.012)
Partner: Tenure	-0.005	-0.001	-0.014
	(0.007)	(0.010)	(0.010)
Fulltime Y/N	-0.897***	-0.986***	-0.796***
	(0.176)	(0.230)	(0.301)
Fulltime Experience	0.035***	0.031**	0.044*
	(0.011)	(0.014)	(0.023)
Tenure	-0.021***	-0.025**	-0.019*
	(0.007)	(0.011)	(0.010)
Children in HH Y/N	-0.237	-0.532**	-0.044
	(0.187)	(0.244)	(0.231)
# Persons in HH	-0.037	0.059	-0.156
	(0.086)	(0.115)	(0.105)
Couple married Y/N	0.393*	0.340	0.424
	(0.212)	(0.276)	(0.271)
East Germany	-0.011	-0.165	0.217
	(0.172)	(0.219)	(0.210)
Years	Yes	Yes	Yes
N	18191	9046	9145

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Standard errors (clustered on household-level) in parentheses.

Table A4.4: Fixed Effects - Controlling for Economic Worries

	FE Pooled	FE Female	FE Male
Partner: Fear of UE Y/N	-0.370**	-0.502**	-0.236
	(0.154)	(0.220)	(0.208)
Big Econ. Worries	-3.413***	-3.099***	-3.793***
	(0.253)	(0.337)	(0.353)
Some Econ. Worries	-1.659***	-1.639***	-1.667***
	(0.172)	(0.241)	(0.236)
Employed Y/N	0.009	-0.063	0.211
	(0.262)	(0.315)	(0.495)
Age	-0.111	-0.143	-0.107
	(0.133)	(0.198)	(0.178)
Education in Years	0.610***	0.590**	0.630*
	(0.224)	(0.288)	(0.348)
Gross Income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Partner: Age	0.080	-0.015	0.084
	(0.135)	(0.251)	(0.177)
Partner: Education in Years	0.029	0.128	0.008
	(0.216)	(0.312)	(0.284)
Partner: Gross Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Partner: Fulltime Y/N	-0.079	-0.256	-0.019
	(0.209)	(0.353)	(0.265)
Partner: Fulltime Experience	-0.020	0.134	-0.092
	(0.041)	(0.143)	(0.057)
Partner: Tenure	0.010	0.012	0.003
	(0.019)	(0.024)	(0.031)
Children in HH Y/N	0.424*	0.390	0.495
	(0.255)	(0.321)	(0.346)
# Persons in HH	-0.346**	-0.154	-0.656***
	(0.143)	(0.177)	(0.196)
Couple married Y/N	0.213	0.328	0.176
	(0.391)	(0.529)	(0.500)
East Germany	1.004	1.246	0.715
	(1.445)	(1.680)	(2.130)
Years	Yes	Yes	Yes
N	38865	20890	17975

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** $p<0.01$; ** $p<0.5$; * $p<0.1$. Standard errors (clustered on household-level) in parentheses.

Table A4.5: MCS Regressions - Proxy: Staff Reductions

	FE Pooled	FE Female	FE Male
Partner: Staff Reduction Y/N	-0.279	-0.291	-0.252
	(0.181)	(0.245)	(0.256)
Big Econ. Worries	-3.475***	-3.306***	-3.687***
	(0.300)	(0.404)	(0.411)
Some Econ. Worries	-1.641***	-1.634***	-1.643***
	(0.204)	(0.288)	(0.275)
Employed Y/N	0.051	-0.040	0.263
	(0.315)	(0.378)	(0.591)
Age	-0.129	-0.089	-0.162
	(0.142)	(0.207)	(0.194)
Education in Years	0.569**	0.635*	0.469
	(0.278)	(0.338)	(0.474)
Gross Income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Partner: Age	0.096	-0.090	0.141
	(0.148)	(0.271)	(0.196)
Partner: Education in Years	0.103	0.178	0.147
	(0.242)	(0.361)	(0.315)
Partner: Gross Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Partner: Fulltime Y/N	0.104	0.018	0.082
	(0.246)	(0.422)	(0.311)
Partner: Fulltime Experience	-0.002	0.172	-0.065
	(0.044)	(0.145)	(0.060)
Partner: Tenure	0.000	0.004	-0.015
	(0.022)	(0.027)	(0.036)
Children in HH Y/N	0.245	0.346	0.143
	(0.291)	(0.370)	(0.401)
# Persons in HH	-0.265	-0.109	-0.535**
	(0.161)	(0.201)	(0.227)
Couple married Y/N	0.257	0.204	0.354
	(0.471)	(0.632)	(0.586)
East Germany	0.658	0.981	0.211
	(1.476)	(1.668)	(2.141)
Years	Yes	Yes	Yes
N	32254	17299	14955

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** $p<0.01$; ** $p<0.5$; * $p<0.1$. Standard errors (clustered on household-level) in parentheses.

Table A4.6: Basic Fixed Effects Regressions

	FE Pooled	FE Female	FE Male
Partner: Fear of UE Y/N	-0.571***	-0.714***	-0.422**
	(0.154)	(0.220)	(0.209)
Employed Y/N	0.029	-0.068	0.296
	(0.265)	(0.318)	(0.497)
Age	-0.101	-0.137	-0.094
	(0.137)	(0.203)	(0.184)
Education in Years	0.598***	0.573**	0.609*
	(0.223)	(0.285)	(0.351)
Gross Income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Partner: Age	0.073	-0.023	0.074
	(0.139)	(0.256)	(0.183)
Partner: Education in Years	0.068	0.154	0.070
	(0.219)	(0.316)	(0.292)
Partner: Gross Income	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
Partner: Fulltime Y/N	-0.039	-0.193	-0.008
	(0.208)	(0.352)	(0.265)
Partner: Fulltime Experience	-0.023	0.134	-0.085
	(0.041)	(0.144)	(0.058)
Partner: Tenure	0.009	0.009	0.003
	(0.019)	(0.024)	(0.032)
Children in HH Y/N	0.406	0.407	0.424
	(0.256)	(0.322)	(0.348)
# Persons in HH	-0.369**	-0.181	-0.666***
	(0.144)	(0.179)	(0.198)
Couple married Y/N	0.236	0.438	0.064
	(0.395)	(0.535)	(0.504)
East Germany	0.701	1.046	0.295
	(1.453)	(1.701)	(2.114)
Years	Yes	Yes	Yes
N	38940	20936	18004

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** p<0.01; ** p<0.5; * p<0.1. Standard errors (clustered on household-level) in parentheses.

Table A4.7: Fixed Effects - Controlling for Own Fear of UE

	FE Pooled	FE Female	FE Male
Big Fear UE	-2.188***	-1.681***	-2.703***
	(0.305)	(0.443)	(0.408)
Some Fear UE	-0.984***	-0.838***	-1.166***
	(0.184)	(0.260)	(0.256)
Partner: Big Fear UE	-0.265	-0.607	0.083
	(0.283)	(0.428)	(0.385)
Partner: Some Fear UE	-0.344*	-0.428	-0.272
	(0.185)	(0.281)	(0.245)
Age	-0.136	-0.277	-0.190
	(0.151)	(0.188)	(0.255)
Education in Years	0.750**	0.350	1.104**
	(0.345)	(0.510)	(0.455)
Gross Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Partner: Age	0.214	0.232	0.114
	(0.145)	(0.249)	(0.207)
Partner: Education in Years	0.083	0.074	0.187
	(0.262)	(0.407)	(0.337)
Partner: Gross Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Partner: Fulltime Y/N	0.038	0.050	0.015
	(0.252)	(0.463)	(0.312)
Partner: Fulltime Experience	-0.066	0.102	-0.116*
	(0.058)	(0.170)	(0.068)
Partner: Tenure	-0.001	-0.011	0.006
	(0.023)	(0.030)	(0.037)
Fulltime Y/N	-0.809***	-1.022***	-0.443
	(0.267)	(0.348)	(0.438)
Fulltime Experience	-0.107*	-0.102	0.049
	(0.063)	(0.078)	(0.175)
Tenure	-0.039	-0.057	-0.032
	(0.026)	(0.042)	(0.034)
Children in HH Y/N	0.116	-0.018	0.287
	(0.325)	(0.415)	(0.403)
# Persons in HH	-0.337*	-0.122	-0.575**
	(0.200)	(0.257)	(0.242)
Couple married Y/N	0.441	0.545	0.463
	(0.480)	(0.668)	(0.571)
East Germany	0.582	1.635	-0.348
	(2.099)	(2.389)	(2.569)
Years	Yes	Yes	Yes
N	27081	13473	13608

Note: Authors' calculations based on the SOEP for the years 2002, 2004, 2008, 2010 and 2012. *** $p<0.01$; ** $p<0.5$; * $p<0.1$. Standard errors (clustered on household-level) in parentheses.

5 How Do Consumers Choose Health Insurance? An Experiment on Heterogeneity in Attribute Tastes and Risk Preferences

5.1 Introduction

Recent policy reforms in the U.S. and in Europe have been directed towards more consumer choice (Cronqvist and Thaler, 2004; Coughlin et al., 2008; Thomson et al., 2013). The underlying reason is that consumers can best express their needs and preferences via their own choices. In the market for health insurance, effective consumer choice is supposed to stimulate price competition among health insurers leading to lower prices and reduced health care expenditure as well as to improved quality. A current example for stimulating consumer choice is the mandatory introduction of health insurance exchanges at state level in the U.S. as a consequence of the Patient Protection and Affordable Care Act of 2010. In these health insurance exchanges individual consumers and small employers are given the opportunity to compare various different plans on an online insurance market platform. It is expected that 13 million people will use the exchanges for choosing health insurance by 2015.[1] Such a reform towards more consumer choice relies on the fact that consumers choose health insurance efficiently.

A similar and well-studied reform is the Medicare Part D Prescription Drug plan within the Medicare Modernization Act of 2003 in the U.S. Having started in 2006, it gives seniors eligible to this plan access to a federally subsidized market for private insurance contracts covering non-mandatory drug prescription. Re-

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[1] Congressional Budget Office: Insurance Coverage Provisions of the Affordable Care Act - CBO's April 2014 Baseline.

sults on the quality of choice from Medicare Part D show that many consumers seem to make suboptimal choices (Abaluck and Gruber, 2011; McWilliams et al., 2011; Heiss et al., 2013). This evidence is in contrast to the standard economic theory where offering more contracts and full information should not make consumers worse off. This distortion can be explained by the fact that health insurance choices are complex due to the variety of different contracts available. Evidence from laboratory experiments shows a negative relationship between the number of contracts offered and decision quality. Schram and Sonnemans (2011) and Besedeš et al. (2012a,b), for instance, show that the quality of choice decreases with an increasing number of health insurance contracts available. Similar results are found in other complex decision scenarios in the field (Iyengar and Kamenica, 2010; Sinaiko and Hirth, 2011). Nevertheless, simply reducing the number of contracts would possibly neglect the fact that consumers differ in their preferences for contract attributes (Besedeš et al., 2012c). In addition, suboptimal choices may also arise from contract attributes, which are difficult to assess. The latter may be deductibles and complementary insurance. Johnson et al. (2013) show for health insurance exchanges that suboptimal choices even persist in a simplified scenario and consequently find that deviations from the optimal contract cannot solely depend on lacking financial literacy. However, the authors pay little attention to explaining this, e.g. by individual risk preferences.

First attempts to reduce complexity while accounting for heterogeneity in preferences have been made in the health insurance exchanges in the U.S. Here, consumers are first asked for individual characteristics and preferences for contract attributes like deductibles. Then they are presented an individual selection of contracts. Evidence from the laboratory and the field supports this approach by demonstrating that individuals themselves use tastes in attributes to reduce complexity. Besedeš et al. (2012a,b) and Ericson and Starc (2012) show that in complex health insurance choices, consumers focus on salient contract attributes and make use of heuristics like choosing the cheapest plan. This finding is in line with a growing body of theoretical and empirical research from behavioral economics, which proposes that when making complex decisions people act on heuristics (see, e.g., Gilovich et al. (2002) or Gigerenzer and Gaissmaier (2011) for overviews). Asking consumers for preferences in attributes might thus be a good way to guide them in reducing complexity while accounting for individual preferences. However, the existing evidence cannot make statements about whether using these heuristics to reduce complexity actually helps people to find contracts which are in line with their individual risk preferences and thus cannot make statements about individual decision quality. While Ericson and Starc (2012) use field data from the Massachusetts health insurance exchanges and cannot account for individual risk preferences, Besedeš et al. (2012a,b) use a laboratory experiment, but do not elicit them. To make statements about the success of individual preselection mechanisms based on contract attributes, it is important to understand how well heuristics actually match individual preferences.

Our objective is to analyze individual behavior in complex health insurance choice decisions and to investigate its relationship with individual risk preferences. For this, we use a controlled laboratory experiment with a sequential design. In the first part of the experiment, similar to Schram and Sonnemans (2011), subjects have to choose insurance in 14 different decision scenarios varying in the number of contracts available. Contracts mirror classic features of health insurance, such as deductibles and complementary insurance. Similar to Abdellaoui et al. (2007); Abdellaoui (2000), and Wakker and Deneffe (1996), we elicit individual choice preferences according to Cumulative Prospect Theory (CPT) in the second part of the experiment. In contrast to previous experimental studies, underlying assumptions of standard Expected Utility Theory (EUT) risk preferences (Schram and Sonnemans, 2011; Besedeš et al., 2012a), we explicitly elicit CPT preferences as they have shown to explain heterogeneity in decisions under risk particularly well. Bruhin et al. (2010), for example, demonstrate that only 20% of the population shows EUT preferences, while the majority demonstrates significant deviations from linear probability weighting which differ in strength and can be explained by Prospect Theory.[2]

Estimating a latent class model to account for heterogeneity in individual tastes for contract attributes reveals five classes. Based on this, we infer distinct behavioral strategies. Most subjects do not evaluate probabilities according to expected payoff maximization (EPM) but assume the worst case and then minimize their costs, i.e., they make use of minimax heuristics. Across classes, we find variations of this strategy differing in the evaluation of certain contract attributes, which are either important to the class members or which they neglect. We can thus give valuable insights into the heterogeneity of tastes in contract attributes. Investigating the relationship between the strategies and individual risk preferences, we find that strategies seem to help consumers to choose contracts, which approximate individual risk preferences.[3] Our results reveal valuable insights for policy makers of how to achieve efficient consumer choice.

The proceedings of the paper are as follows. In Section 5.2, we describe the exper-

[2] See also Conte et al. (2011) finding heterogeneity in risk-aversion parameter and weighting function parameter for choices under risk. They also identify only 20% of the observations being EUT types, while 80% can be captured by Rank Dependent EUT.

[3] This complementary relationship between CPT and decision rules is also found by Suter et al. (2013).

imental design. Section 5.3 describes the procedure. In section 5.4, we report our results before we conclude in section 5.5.

5.2 Experimental Design

The experiment consists of two parts without any interaction between subjects. The first part of the experiment captures subjects' insurance choices in 14 individual decision situations varying in the degree of complexity. The second part serves to determine risk preferences according to CPT for each subject. It contains 72 lottery choices. The sequential design allows for two things. First, we can analyze health insurance choice behavior with a special focus on underlying heterogeneity in attribute tastes. Second, we can investigate the predictive power of individual CPT preferences for health insurance choices and the relationship to behavioral strategies.

5.2.1 Experimental Conditions

Health Insurance Choices

In each decision, subjects have to buy a health insurance contract. The decision framework and contract attributes are modeled similarly to Schram and Sonnemans (2011). Decisions vary in the complexity, that is the number of contracts available to choose from, ranging from 2 to 12. They occur in a sequence that is randomly determined and the same across all sessions. To buy a health insurance contract, subjects have to bear costs in form of a premium. In addition, depending on the characteristics of the chosen contract, treatment costs in case of illness are either paid by the subject, the health insurance or a combination of both. We abstract from other monetary and non-monetary costs that may go along with an illness, such as missing wages or pain. Contracts vary in their attributes, i.e., their premium, complementary insurance for certain illnesses, and deductibles. In total, there are 5 illnesses A, B, C, D, and E, each of which can occur with a certain probability that remains unchanged across all decisions. Thus, individuals face risky decisions with potential losses.

Each health insurance contract consists of a basic and a complementary health insurance. While the basic insurance always covers treatment costs of illnesses A, B, and C, the complementary insurance can additionally cover treatment costs of illnesses D and E. Table 5.1 illustrates the contract attributes: the diseases covered by basic and complementary insurance, their probabilities of occurrence and their

Table 5.1: Basic Decision Situation

Disease	Probability of Occurrence	Treatment Costs without Insurance
Basic Insurance		
A	5 %	60
B	20 %	40
C	50 %	20
Complementary Insurance		
D	1 %	2000
E	20 %	50

treatment costs without insurance.[4] Moreover, we introduce deductibles of 0, 10, or 30. In our scenario, a deductible refers to the three illnesses associated with the basic insurance. In case of occurrence of illness A, B, C, or a combination of them, a subject has to pay the accruing treatment costs up to the amount of the deductible; the health insurance pays the amount in excess. Depending on the contract, a subject has to pay the premium, the potential treatment costs up to the amount of the deductible under the basic insurance and the costs for the illnesses D and E if not covered by complementary insurance. For the full set of the instructions, see Appendix II.

By combining all attributes except for the premium, we obtain 12 unique health insurance contracts. For each of these 12 contracts, we calculate the fair premium. To induce a rank-ordering with respect to subjects' expected payoff value - for expected payoff maximizing (EPM) decision makers some contracts are preferred to others - we add a margin to the fair premium. We increase the variation in contracts by reproducing the 12 unique contracts to 48 contracts and add a different margin to each contract's fair premium. This way, we obtain a different rank ordering in each of the four sets and a total number of 48 distinct contracts. The contracts offered in a decision are randomly chosen from one of these four different sets. Contracts that are dominated in their cumulative prospect value and the EPM value are excluded.[5]

[4] Values of contract attributes are measured in *Taler*, our laboratory currency.

[5] To calculate ex-ante CPT values, we use the parameters from Tversky and Kahneman (1992). For a detailed explanation of the contract design, see Appendix I.

Lotteries
In the second part of the experiment, subjects face 72 lottery decisions modeled according to Abdellaoui et al. (2007); Abdellaoui (2000), and Wakker and Deneffe (1996). In each of the decisions, subjects are presented with two alternatives from which they have to choose one. The two alternatives can either be two lotteries, or one lottery and one fixed payoff. The values of the payoffs can be either positive or negative. The first 24 payoffs are positive, the following 6 are mixed, and the last 42 are negative. This composition of lotteries allows us to determine individual parameters for the value and weighting function.[6]

Robustness Check
To make sure that results are not driven by framing effects, we also design a neutral experimental condition for the first part. The decision rounds are identical except for the wording. While the health framing condition contains health insurance contracts and treatment costs, the neutrally framed condition contains insurance contracts and costs in case of damage. Although framing should not make a difference for a rational decision maker, previous evidence has shown that there may be context dependency.

5.2.2 Payment

All monetary amounts in the experiment are indicated in the experimental currency Taler. 1 Taler equals Euro 0.50. In order to avoid wealth or averaging effects, we follow the standard of applying the random payment technique at the end of the experiment.[7]
Similar to previous studies dealing with losses, we endow each participant with an initial amount of money for each part. In experiments, this is a common approach to model losses. Etchart-Vincent and l'Haridon (2011) show that results do not differ essentially between bearing losses from an endowment and real losses. In particular, this means that participants integrate their endowment and evaluate costs as losses.
For the first part, one health insurance decision is randomly chosen to be payment-relevant. For each illness within this decision, it is then randomly determined whether a subject suffers from it or not. Subjects' total costs in this part are detracted from the initial endowment of 2200 Taler. Afterwards, three decisions of

[6]Note that as we aim at analyzing decisions over losses, we focus on the negative lotteries to benefit from more accuracy in the negative domain.
[7]Various research studies confirm that the random payment technique does not dilute the power of the monetary incentives for non-complex choice tasks (Starmer and Sugden, 1991; Cubitt et al., 1998; Laury, 2005; Baltussen et al., 2012).

the second part are randomly chosen to be payment-relevant. One of these is drawn from the positive, one from the mixed, and one from the negative lotteries. Realized losses from the lotteries are subtracted from the sum of realized gains and the initial endowment of 3500 Taler. Total earnings comprise subjects' final payments for the randomly determined decisions in both parts of the experiment.

5.3 Experimental Procedure

The computerized experiment was programmed with z-Tree (Fischbacher, 2007) and conducted at elfe, the Essen Laboratory for Experimental Economics at the University of Duisburg-Essen, Germany in 2014. Overall 113 students from the University of Duisburg-Essen participated in five sessions (56 participants in the health treatment, 57 participants in the general treatment. Participants were recruited by the online recruiting system ORSEE (Greiner, 2004).

The procedure was as follows: Upon arrival, subjects were randomly allocated to their seats in the laboratory. They were given the corresponding instructions previous to each part of the experiment and were given time to read the instructions and to ask comprehension questions. The latter were answered in private by the same one experimenter across all treatments. To assure subjects' understanding of the decision task in each part, they had to answer a set of control questions. The experiment did not start unless all subjects had answered the control questions correctly. At the end of the experiment, subjects were asked to answer a short questionnaire including demographics and questions directly linked to their behavior in the previous decisions. In both parts subjects had access to calculators. In order to control for the use of them within the experiment, we asked about whether they had utilized them in the subsequent questionnaire. Sessions lasted for about 90 minutes. Subjects earned, on average, Euro 25.62.

5.4 Results

5.4.1 Insurance Choice Behavior

Aggregate Behavior

To begin with, we show descriptive statistics for health insurance choice behavior using the aggregated data. Specifically, we are interested in the contract attributes that are important for consumers when choosing health insurance. For this, we examine the potential losses of 2000 and 50 (illness D and E) as well as the deductibles of 0, 10, and 30 as representative of the basic insurance (illness A, B,

Table 5.2: Attribute Means for Actual Choices and Expected EPM Contracts

	Mean Conditional Decisions
Premium	
Premium	83.35
	(34.52)
Complementary Insurance	
Loss of 2000 [1%]	0.66
	(0.47)
Loss of 50 [20%]	0.75
	(0.43)
Deductibles	
Deductible 0	0.26
	(0.44)
Deductible 10	0.21
	(0.41)
Deductible 30	0.52
	(0.50)

Note: Standard deviations are provided in parentheses. Probability of occurrence in square brackets.

and C). Table 5.2 summarizes the mean premium and shares of how often subjects choose these attributes across all decisions. Note that due to our contract design, in some decision rounds all contracts are equal regarding a specific attribute. Therefore, we exclude these decisions and calculate means and standard deviations, provided that subjects were given the opportunity to decide on whether or not an attribute should be covered.

We observe that the coverage of the complementary insurance is high in actual chosen contracts and thus appears to be important for consumers; the attributes connected to the potential loss of 2000 and the potential loss of 50 are covered in 66% and 75% of all choices. Furthermore, we find a large percentage of actual choices including a deductible of 30 (52%). Fewer choices contain contracts including no deductible (26%) and a deductible of 10 (21%). However, the analysis based on averages of actual chosen attributes is rather limited since we expect heterogeneity in attribute tastes.

Latent Class Logit Model (LC-logit)

To investigate individual choice behavior and to assess heterogeneity in attribute tastes, we apply a model that is capable of providing insights in the underlying preference structure in our sample. The latent class logit (LC-logit) model allows us to identify differences in tastes across individuals. It is widely used in health economics applications to identify heterogeneity (Deb and Trivedi, 2002;

Bago d'Uva, 2005, 2006; Bago d'Uva and Jones, 2009; Greene et al., 2014; Lagarde, 2013). The model estimates a probability of belonging to some (homogenous) class in the sample. These classes are generated endogenously based on underlying individual characteristics with the aim of achieving within-class homogeneity. In our case, the tastes in contract attributes - premium, insurance of the possible losses of 2000 and 50, and deductibles - are considered. Furthermore, we control for possible treatment effects by using a binary indicator of treatment.

Following Pacifico and Yoo (2012), we use the stata routine LC-logit to estimate the model. In this model, each of N respondents in the experiment faces J alternatives (contracts) in each of the D health insurance choice decisions. A binary choice indicator, y_{njd} is created, which becomes 1 if the respondent n chooses j in decision d. x_{njd} contains the contract specific attributes. Furthermore, respondents are characterized by z_n, which includes a constant and variables that are invariant across decisions for the respondents, e.g. the binary indicator for treatment.

As indicated, the model assumes that there is a number of classes C of different attribute tastes, $\beta = \beta_1, \beta_2, \ldots \beta_C$. Under the condition that respondent n is in class c, the probability of $n's$ choice sequence can be written as a product of conditional logit formulas.

$$P_n(\beta_c) = \prod_{d=1}^{D} \prod_{j=1}^{J} \left(\frac{exp(\beta_c x_{njd})}{\sum_{k=1}^{J} exp(\beta_c x_{nkd})} \right)^{y_{njd}} \tag{5.1}$$

As we do not know which class a respondent belongs to, we must specify the unconditional likelihood of respondent n's choices, i.e. the weighted average of the previous equation over all classes. The weight for a specific class c is the fraction of the population and modeled as fractional multinomial logit:

$$\pi_{cn}(\theta) = \frac{exp(\theta_c z_n)}{1 + \sum_{l=1}^{C-1} exp(\theta_l z_n)} \tag{5.2}$$

where $\theta = (\theta_1, \theta_2, \ldots, \theta_{(C-1)})$ are class membership model parameters.[8] Summing up the log unconditional likelihood of each respondent yields the sample log likelihood.

$$\ln L(\beta, \theta) = \sum_{n=1}^{N} \ln \sum_{c=1}^{C} \pi_{cn}(\theta) P_n(\beta_c) \tag{5.3}$$

The optimal number of homogenous classes is identified by applying the Bayesian Information Criterion (BIC). In our analysis, the BIC suggests to define five groups. The LC-logit model estimates coefficients for each of the five classes. The coeffi-

[8] θ_C is normalized to zero for identification.

cients can then be used to determine the average in-class willingness to pay (WTP) for certain attributes. Thus, the model allows us to analyze heterogeneity by considering distinct WTP-values for each single class, and hence to infer different behavioral types on basis of their attribute preferences, while not neglecting the complexity of the task itself.

Heterogeneity in Individual Insurance Choice Behavior

As previously indicated, classes are built based on underlying parameters. We include contract attributes and control for framing effects. Table 5.3 presents the estimation results.

Table 5.3: Latent Class Logit Model - Results

	Class 1	Class 2	Class 3	Class 4	Class 5
Premium	0.134^{***}	0.044^{***}	0.062^{***}	0.029^{***}	0.099^{***}
	(0.019)	(0.004)	(0.008)	(0.004)	(0.011)
Potential loss of 2000	-0.573	-3.905^{***}	-2.177^{***}	-2.645^{***}	-1.681^{***}
	(0.412)	(0.344)	(0.239)	(0.224)	(0.366)
Potential loss of 50	-4.654^{***}	-4.068^{***}	-2.590^{***}	-1.140^{***}	-0.683^{**}
	(0.705)	(0.570)	(0.257)	(0.268)	(0.345)
Deductible of 10	-2.307^{***}	-0.436^{**}	-0.680^{***}	0.049	-0.883^{***}
	(0.462)	(0.204)	(0.228)	(0.204)	(0.340)
Deductible of 30	-4.771^{***}	-1.226^{***}	-1.766^{***}	-0.517^{**}	-2.086^{***}
	(0.870)	(0.224)	(0.366)	(0.232)	(0.437)
Health Framing	-0.104	-0.233	0.597	-0.534	
	(0.892)	(0.682)	(0.795)	(0.783)	
Class share	0.097	0.361	0.196	0.231	0.116

Note: Latent class logit model estimated using Stata's lclogit command. N= 10.170. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors calculated by gllamm and provided in parentheses.

The coefficients of health framing are not significantly different from zero. The LC-logit identifies five classes with different class sizes. Class 1 makes up 9.7% of all subjects, classes 2 to 5 include 36.1%, 19.6%, 23.1%, and 11.6% of all subjects, respectively. However, interpreting the results from the LC-logit model is tedious as we cannot directly quantify effects. Hence, we calculate the WTP, i.e. the amount (in Taler) a subject is willing to forgo to insure a certain attribute. In particular, the WTP is calculated for the attributes within each class by dividing each attribute's coefficient by the coefficient of the premium, i.e. $\widehat{WTP_i} = \hat{\beta}_i / \hat{\beta}_{premium}$. We find a considerable degree of heterogeneity as the WTP differs substantially across the five classes. Moreover, we observe that while some WTP values exceed the WTP value of a risk-neutral expected payoff maximizing decision maker (certainty equivalent, CE), others are substantially lower.

Exploiting heterogeneity in tastes for contract attributes, we investigate health insurance choice behavior on class level. For this, we account for the fact that health insurance choices in our scenario are difficult with respect to evaluating attributes like complementary insurance covering large losses occurring with small probabilities, or deductibles implying conditional probabilities. As previous evidence suggests that people use simplifying strategies, or heuristics, in such complex decision scenarios we account for behavioral strategies.[9]

For decisions under risk, two types of strategies seem reasonable, expected payoff maximization (EPM) and minimax. To distinguish between EPM and minimax we compare the WTP values with the certainty equivalent (CE). WTP values for each class and the CE are provided in Table 5.4. Individuals following EPM integrate probabilities and choose the contract that provides the highest expected payoff. WTP values for a class that behave according the EPM strategy should not substantially differ from the CE. Quite differently, the pure minimax players ignore information on all probabilities and choose a contract that induces the highest outcome in the worst situation, i.e. the lowest treatment costs in case of suffering from all illnesses. This strategy is widely found in the literature and is similar to the priority heuristic (Brandstätter et al., 2006) as well as to the minimax regret theory (Savage, 1954; Braun and Muermann, 2004; Hayashi, 2008).[10] Comparing WTP values with the CE reveals that there is only a small difference for class 5.[11] Thus, class 5 seems to integrate probabilities and can be classified as using an EPM strategy. All other classes differ in their WTP values from the CE for a majority of attributes and seem not to integrate probabilities.

Moreover, previous literature has shown that people focus on salient attributes (Tversky and Kahneman, 1973; Hensher, 2006). In our scenario, especially the attribute of potential loss of 2000 occurring with a 1% probability is a salient attribute, as it is by far the biggest stake. This might affect the minimax strategy in three ways. First, the combination of the potential loss of 2000 and the simplicity to evaluate it with 1% probability may make it more prone to being evaluated properly compared to other attributes. We might thus expect a minimax strategy where the 2000 is highly integrated. Furthermore, concerning this attribute, Tversky and Kahneman (1992) note that "... the (weighting) function is not well-behaved near the endpoints, and very small probabilities can be either greatly overweighted or neglected altogether" (p. 303). According to this, one could find WTP values for this attribute to be either extremely high, or extremely low. Extremely high WTP

[9]See, e.g. Gigerenzer and Gaissmaier (2011) for an overview.

[10]In general, the priority heuristic simplifies to minimax if no aspiration level is assumed and the preliminary step is omitted, where differences in the expected values are observed.

[11]The CE values are within the 5% confidence interval.

Table 5.4: Willingness to Pay for Attributes by Class

	Class 1 N = 11	Class 2 N = 44	Class 3 N = 21	Class 4 N = 24	Class 5 N = 13	CE (EPM)
Complement. Ins.						
Loss of 2000	4.27	89.55	35.16	89.79	17.07	20
(1%)	[-1.58, 10.13]	[78.14, 100.97]	[26.16, 44.16]	[68.92, 110.67]	[11.22, 22.92]	
Loss of 50 (20%)	34.73	93.29	41.82	38.69	6.93	10
	[29.38, 40.09]	[73.84, 112.73]	[32.50, 51.15]	[21.41, 55.98]	[0.79, 13.08]	
Deductibles						
Deductible 10	17.22	9.99	10.98	-1.67	8.96	6.2
	[10.78, 23.66]	[0.59, 19.39]	[3.16, 18.80]	[-15.27, 11.94]	[2.27, 15.65]	
Deductible 30	35.60	28.11	28.52	17.55	21.17	14.8
	[28.60, 42.60]	[20.07, 36.15]	[20.72, 36.32]	[4.24, 30.87]	[14.32, 28.03]	

Note: 5% confidence intervals are provided in square brackets.

values would correspond to the pure minimax strategy where the probability of 1% is greatly overweighted and thus, the attribute is covered in any case. The importance of this strategy is also underlined by the fact that on aggregate, 66% of subjects choose contracts covering the potential loss of 2000. In contrast, extremely low WTP values of the salient attribute would indicate that the probability of 1% is greatly underweighted and thus, the attribute is ignored and not part of outcome calculation. In a theoretical approach by Etner and Jeleva (2014) these types are called fatalists, as they would invest less in insurance than EPM types.

For class 1, we find that subjects do not integrate probabilities and ignore the salient attribute of potential loss of 2000 as the WTP is small and insignificant. Thus, class 1 follows a minimax strategy ignoring the potential loss of 2000 - the *fatalist minimax* strategy. This strategy highly relates to observations made by Kunreuther and Pauly (2014), who stress the tendency to ignore low-probability events with high-consequences in health insurance markets. We also find the opposite, respondents who overweight this small probability in classes 2 and 4, where the WTP values substantially exceed the CE. For class 2 all WTP values exceed the CE as participants use a minimax strategy that covers the potential loss of 2000 - *pure minimax* strategy. Class 4 differs from class 2 by ignoring the deductible of 10 -the *minimax ignoring deductible 10* strategy. Class 3 seems to be a hybrid class in the sense that participants seem to evaluate the salient attribute of 2000 properly but ignore all other probabilities - the *moderate minimax* strategy.

To quantify the predictive power of the five behavioral strategies, Table 5.5 shows the average fraction of observed choices in accordance with the strategies for the corresponding class over all decisions. Note that in some decisions, one contract may be favored by several strategies.[12] Table 5.5 shows that strategies have a high

[12]Double counting cannot be totally avoided a priori since strategies are inferred endogenously.

Table 5.5: Percentages of Choices in Accordance with Behavioral Strategies

	Class 1 N = 11	Class 2 N = 44	Class 3 N = 21	Class 4 N = 24	Class 5 N = 13
	Fatalist minimax	*Pure minimax*	*Moderate minimax*	*Minimax ignoring deductible 10*	*EPM*
Fatalist minimax	**0.75**	0.24	0.50	0.19	0.40
Pure minimax	0.16	**0.79**	0.42	0.54	0.08
Moderate minimax	0.67	0.48	**0.62**	0.34	0.42
Minimax ignoring deductible 10	0.16	0.77	0.40	**0.57**	0.08
EPM	0.57	0.16	0.39	0.23	**0.79**

explanation power within their respective class.[13]
As types of minimax strategies are closely interrelated, we find similar fractions for some of them across the respective classes. In particular, following minimax or minimax ignoring deductible 10 are closely related. Also, fatalist minimax and moderate minimax are related to each other and to the EPM strategy to some extent. Considering the whole sample, 53% of all choices can be explained by minimax heuristics. In comparison, 42% of all actual choices are in line with expected payoff maximization behavior.

5.4.2 Individual Choice Behavior and CPT-Risk Preferences

We now turn to investigating the relationship between individual choice behavior and Cumulative Prospect Theory (CPT). For this, we use the individual CPT risk preferences elicited in the lottery part of the experiment to calculate subjects' individual weighting and value functions. Based on these functions, we compute the individual CPT values for each available contract in the health insurance choice part. This allows an individual rank ordering of contracts with respect to each subject's CPT-values, whereby the individual contract with the highest CPT-value is captured by rank 1. This rank order serves as a quality benchmark. The contract

[13]In the vast majority off all decisions, a behavioral strategy predicts a unique contract. Just in two decisions, two strategies, moderate minimax and EPM, predict more than one single contract.

Table 5.6: Fixed Effects Regression Model - Behavioral Strategies and Complexity

	Class 1 N = 11	Class 2 N = 44	Class 3 N = 21	Class 4 N = 24	Class 5 N = 13
Number of contracts	0.206*** (0.0546)	0.129*** (0.0108)	0.168*** (0.0278)	0.186*** (0.0286)	0.101*** (0.0325)
Fatalist minimax	0.576 (0.421)				
Pure minimax		-0.919*** (0.202)			
Moderate minimax			-0.358 (0.214)		
Minimax ignoring deductible 10				-0.645*** (0.174)	
EPM					-0.721*** (0.216)
N	154	616	294	336	182
R^2	0.166	0.252	0.116	0.230	0.096

Note: Standard errors (clustered on individual level) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

expected by CPT (rank 1) is chosen in 41.7% of all decisions. Participants opt for the best or the second best rank in the majority of all choices (71.9%). Thus, CPT preferences can explain individual health insurance choices to a substantial extent. While CPT apparently has considerable predictive power for health insurance choices on its own, we aim at investigating the relationship between CPT-preferences, behavioral strategies, and complexity. Therefore, we use panel regression techniques to explain the rank of the chosen contract by the assigned behavioral strategies and the number of contracts on class level. We interpret the decision rounds as quasi panel and use individual fixed effects to account for decision-invariant individual heterogeneity. The strategies assigned to each class enter as dummy variable that equals 1 if the respondent chooses the contract expected by the assigned strategy. Table 5.6 reports the coefficients on the rank according to CPT.
We find that increasing the number of contracts has a highly significant positive effect on the rank across all classes, i.e., it increases deviation from the contract with the highest CPT value. This result confirms the expected negative relationship between number of contracts and decision quality. Acting on the assigned strategy has a negative coefficient, which translates into a decrease in deviation, except for class 1. For class 3, the point estimate is negative and insignificant. That is, acting in line with strategies predominantly enables individuals to come closer to their

CPT-optimal contract. Thus, behavioral strategies serve well as approximations of CPT behavior (or vice versa) in decision situations where certain attributes are difficult to evaluate.

5.4.3 Robustness Checks

Finally, we control for the robustness of our results with respect to the framing, gender and the use of a calculator using two-sided Mann Whitney tests. First, we test for differences in the distribution of actual choices between the health and the neutral experimental condition. In 12 of 14 decisions, we do not find any significant difference in choice making behavior (p = 0.128). In 2 decisions a weak significant difference is observed (p = 0.077). Furthermore, we control for differences in choice making behavior by gender and find no significant difference (p = 0.157). Last, we control for using a calculator. A two-sided Mann Whitney test reveals only in 2 of 14 decisions significant differences in choice making between subjects using a calculator and subjects that do not use one (p = 0.03).

5.5 Conclusion

In this study, we conduct a laboratory experiment with a sequential design to investigate the relationship between behavioral strategies and CPT risk preferences. Using a latent class model, we identify five classes demonstrating substantial heterogeneity in subjects' preferences for contract attributes. From this, we infer distinct behavioral strategies. In line with Bruhin et al. (2010), we find that a minority of subjects of about 15% are rational EPM decision makers while the majority show variations of minimax heuristics. Investigating the relationship of insurance choice behavior and CPT risk preferences, we find that individual CPT risk preferences perform well in predicting health insurance choices. In particular, CPT predicts the chosen contract for roughly 40%; considering first and second best contracts, CPT's predictive power even accounts to 70%. Analyzing the relationship between strategies and individual risk preferences shows that when increasing complexity, strategies help individuals to approximate their individual CPT preferences. Thus, we provide novel evidence to the strand of research of investigating individual health insurance choice behavior and heuristics, such as Ericson and Starc (2012) and Besedeš et al. (2012a,b). However, we cannot say whether subjects were not able to optimize by maximizing expected payoffs due to a lack of knowledge, or whether they were simply unwilling to do so as they prefer heuristics. Future research should asses this. Our results also give insights to policy makers for how to achieve efficient consumer choice. In the light of substantial heterogeneity in tastes for attributes, market places should acknowledge offering various contract options. While previous evidence has shown that increasing the number of health insurance contracts offered leads to worse decision quality (Schram and Sonnemans, 2011; Besedeš et al., 2012a,b), we find that individuals are heterogeneous in their tastes for contract attributes and apply simplifying strategies helping them to approximate their individual CPT risk preferences. Our results suggest that when setting rules in the insurance sector to decrease complexity, one should be careful not to restrict the number of contracts too much in order to account for the heterogeneity in tastes for contract attributes. Moreover, our results shed light on contract pre-selection mechanisms based on individual preferences for contract attributes as in the U.S. health insurance exchanges. According to our results, asking for preferences in certain contract attributes first, and then only showing an individual pre-selection, might be a successful way to balance complexity and heterogeneity in preferences and thus achieve efficient consumer choice. The latter can then stimulate competition among health insurance providers and reduce costs in the health care market.

5.6 Appendix

5.6.1 Appendix I: Design of Contracts and Decisions

We generate four different sets of contracts (I, II, III, IV) which differ in rank ordering according to expected payoff maximization (EPM). This gives 48 possible contracts in total. Table A5.1 provides an overview of all possible contracts organized in the four sets. Set IV serves as control and is designed to have identical EPM values for each of the 12 contracts under consideration.[14] To avoid participants to remember contracts from the previous decision, all contracts offered in a decision round are selected from one of these sets; the actual set alternates between the decision rounds. Table A5.2 provides an overview of all 14 decision situations ordered according to the number of available contracts to choose from. The table provides information about the contract characteristics of a decision situation. In addition, contracts predicted by the behavioral strategies and most frequently chosen contracts are provided. Furthermore, the most frequently predicted contracts based on individual Cumulative Prospect Theory (CPT) values elicited in the lottery part are presented. For a comparison CPT values from Tversky and Kahneman (1992) are given. Note that the labels of contracts refer to the columns in Table A5.1. For example, the most frequent chosen contract in the decision offering 9 available options refers to column 4 in Table A5.1.

5.6.2 Appendix II: Instructions and Comprehension Questions

Note that instructions for the first part of the experiment are provided jointly for the non-health and the health framing. Words that differ in the health framing instructions are indicated in brackets.

Welcome to the Experiment!

Preliminary Remarks
You are participating in a study of choice behavior for the purposes of experimental economic research. During the experiment you and the other participants are asked to take decisions. In doing so, you can earn money. The resulting amount is depending on your decisions. After finishing the experiment, your total earnings will be converted into Euro and paid cash. For this experiment all amounts are designated as Taler, the laboratory currency, where 100 Taler translate to 0.50

[14]The EPM values are not strictly equal, since we round the premiums in order to generate integers.

Euro. The experiment will take around 135 minutes and consists of two parts. Before each of the two parts, you will receive detailed instructions. Note, that neither your decisions made in part one nor the decisions made in part two will have an influence for the respective other part. Moreover, there are neither right nor wrong answers in any of the two parts.

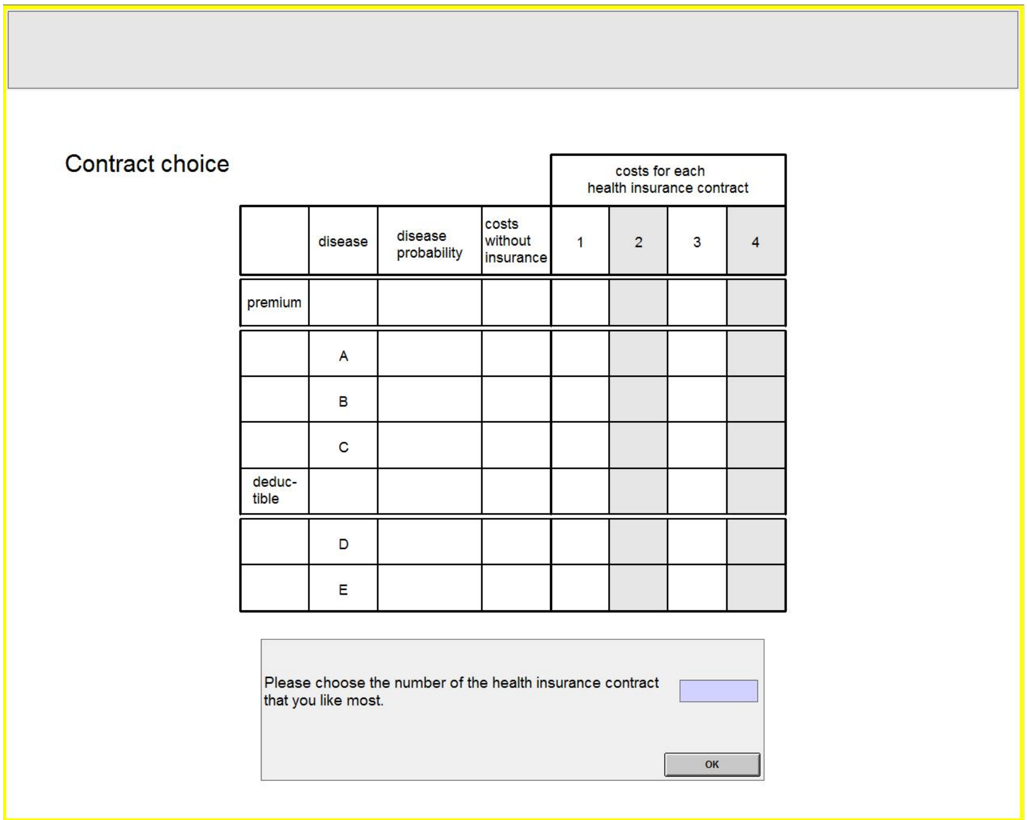
Part I

Please read the following instructions carefully. Approximately five minutes after handing out the instructions, we will approach you to answer any unresolved issues. In case you have any questions along the experiment, please feel free to call attention for yourself by raising your hand. We will come to your seat to answer open questions. For this part you will be endowed with 2200 Taler.

Description of Decision-Rounds
As a [health] insurance holder, you have to choose one [health] insurance contract in each of the 14 decision rounds. Depending on the round, the number of offered contracts may vary between 2 and 12. By purchasing a [health] insurance contract you have to pay a premium, for which you are entitled to receive [health] insurance benefits in case of [illness] damage. Further, [treatment] costs may be occasioned in case of [illness] damage. Depending on the benefits of the chosen contract, [treatment] costs are borne by either your [health] insurance or yourself.

[Health] Insurance Contracts
The [health] insurance contracts may differ in both, the height of the premium and the benefits, which you are entitled to receive from your insurance in case of [illness] damage. Thereby the premium corresponds to the price you pay for the respective [health] insurance contract. Each contract offers specific benefits, i.e. coverage of certain [treatment-] damage-costs in case of [illness] damage. The different [health] insurance contracts from which you can choose are displayed in a table on your screen. The premiums for the particular contracts can be seen from the identically named row. An exemplary decision screen, without any entries, is depicted on the next page.

[Illnesses] Damages
In total [you can catch five illnesses] there are five possible damages, denoted A, B, C, D, and E. Each [disease] damage occurs with a probability, which is unchanged along the decision rounds. Whether [you catch the disease] a damage occurs in a round depends on these probabilities. From the respective columns on your



screen, you can see both, the [illness] damage as well as the associated probability. It is possible [to catch] that none or even more than one [disease] damage occurs in a round. After finishing the experiment one decision round is determined as being relevant for payment. Subsequently, a random number generator determines for each [disease] damage whether [you fall ill] it occurs in the round, which has been ascertained as being payment relevant priory. Therefore, the random number generator draws an equally probable number between 1 and 100 for each of the five [diseases] damages. If the drawn number is smaller or equal to the associated probability of [catching the disease] occurrence, [you fall ill] the damage occurs in this round. If the drawn number is larger than the associated probability of the [disease] damage, [you will not fall ill] it does not occur. Whether or not [you caught a disease] a damage occurs in the round, which is relevant for payment will be displayed on your screen after the second part of the experiment.

Benefits in Case of Damage [Illness]

When [you catch a disease] a damage occurs, it occasions [treatment] costs. As shown in the exemplary decision screen, [treatment] costs of the [diseases] damages in case of [illness] damage can be read off the column titled "Costs without Insurance". By paying your premium you are entitled to receive [health] insurance benefits in case of [illness] damage. Each [health] insurance contract consists of a basic and a complementary insurance: [Diseases] Damages A, B and C are covered by basic insurance in all contracts. That is, [treatment] costs in case of [illness] damage are incurred by the health insurance. As complementary insurance, some contracts offer coverage of [treatment] costs for [diseases] damages D and E. Additionally, some [health] insurance contracts include deductibles for the [treatment] costs from the [diseases] damages covered by basic insurance. A deductible means that you as an insurance holder have to bear the [treatment] costs for the basically insured [diseases] damages A, B and C up to the amount of the deductible in case of [illness] damage. If the sum of [treatment] costs for [diseases] damages A, B and C is larger than the amount of the deductible, you only have to pay treatment costs up to the amount of the deductible. If the sum of [treatment] costs is smaller than the deductible, you bear the complete costs. You find the deductible corresponding to the [health] insurance contract in the identically named row. The total costs that you have to bear per decision round is determined as the sum of the premium of your chosen contract, possible deductibles and [treatment] costs for non-insured [diseases] damages in case of [illness] damage. The total costs for the round which is relevant for payment will be displayed on your screen after the second part of the experiment.

Earnings

After the experiment a random number generator draws one from the 14 decision rounds, which is relevant for payment. For this decision round you have to pay for the premium of your chosen contract, possible deductibles and [treatment] costs for non-insured [diseases] damages using your 2200 Taler. That is, all occurring costs of your chosen [health] insurance contract and [possibly caught diseases] possible damages of this round are added up. These total costs are then subtracted from your 2200 Taler. The residual will be paid to you cash after the experiment together with your earnings from the second part of the experiment.

Comprehension Questions

Prior to the decision rounds, we would like to ask you to answer six comprehension questions. These comprehension questions are intended to facilitate your familiarization with the decision situation. Please note that comprehension questions do not serve as guidance for the experiment. They are solely intended to sharpen your mind with respect to the decision situations which come up along the experiment. The entries that appear in the comprehensive questions are different from those in the experiment.

Part II

Please read the following instructions carefully. Approximately five minutes after handing out the instructions, we will approach you to answer any unresolved issues. In case you have any questions along the experiment, please feel free to call attention for yourself by raising your hand. We will come to your seat to answer open questions. For this part you will be endowed with 3500 Taler.

Description of Decision Rounds

In this part of the experiment, we ask you to participate in 72 decision rounds. In each of the 72 round, you will be shown two alternatives on your screen, alternative L on the left-hand side and alternative R on the right-hand side. Each time you must choose the one alternative that you prefer. There are two possibilities of how the alternatives are designed:

- First, both alternatives are lotteries. A lottery consists of two payoffs, whereat one payoff is shaded red and the other payoff is shaded blue. Which one of the two payoffs is drawn depends on probabilities of occurrence, which are displayed on your screen.
- Second, one lottery and one safe payoff. A safe payoff is a single value, which occurs with 100% probability and is shaded gray.

The payoff values may be positive or negative for both, lotteries and safe payoffs. The first 24 decision rounds include only positive payoff values. The subsequent six decision rounds are mixed, i.e. they feature positive as well as negative payoff values. Afterwards, 42 decision rounds with only negative payoff values are shown. Positive values translate to gains while negative values stand for losses. The payoffs as well as the probabilities of occurrence may change along the rounds.

Probabilities of Occurrence

To convey a sense of the probabilities of occurrence, they are illustrated as pie chart between alternative L and alternative R on your screen. Thereby, the red area corresponds to the probability that the red payoff is drawn. Analogous, the probability for the blue payoff is depicted in the blue area. Additionally, the probabilities are given as number on the lines of the respective payoffs. Safe payoffs are safe and as such have a probability of 100%, if you choose this option.

Earnings

Subsequently to part two and after the draw for the payoffs in part I, a random number generator draws three of your chosen lotteries. These are relevant for payment. Thereby, one lottery is randomly drawn from the 24 positive decision rounds, one from the six mixed rounds and another one from the 42 negative decision rounds. If the drawn lottery is not a safe payoff, another random number generator determines for each lottery whether the red or the blue payoff occurs. These ascertained payoffs are subtracted from your 3500 Taler, if negative and added if positive. The result is your earning from part two. Your total earnings from part one and part two of the experiment is the sum of your earnings from both parts and is paid to you in cash after the second part of the experiment.

Comprehension Questions

Prior to the decision rounds, we would like to ask you to answer two comprehension questions. These comprehension questions are intended to facilitate your familiarization with the decision situation. Please note that comprehension questions do not serve as a guidance for the experiment. They are solely intended to sharpen your mind with respect to the decision situations which come up along the experiment. The entries that appear in the comprehensive questions are different from those in the experiment.

Table A5.1: Possible Contracts in the Experiment

	1	2	3	4	5	6	7	8	9	10	11	12
Premium I	111	161	149	100	135	55	62	29	105	84	35	50
Premium II	167	105	85	56	71	139	30	89	89	100	115	30
Premium III	159	81	157	120	95	75	90	49	25	36	83	106
Premium IV	91	85	81	76	75	71	66	65	61	56	55	46
A							0					
B							0					
C							0					
Deductibles	0	10	0	30	10	0	30	10	0	30	10	30
D	0	0	0	0	0	2000	0	2000	2000	2000	2000	2000
E	0	0	50	0	50	0	50	0	50	0	50	50
EPM-Value I	-111	-167.2	-159	-114.8	-151.2	-75	-86.8	-55.2	-135	-118.8	-71.2	-94.8
EPM-Value II	-167	-111.2	-95	-70.8	-87.2	-159	-54.8	-115.2	-119	-134.8	-151.2	-74.8
EPM-Value III	-159	-87.2	-167	-134.8	-111.2	-95	-114.8	-75.2	-55	-70.8	-119.2	-150.8
EPM-Value IV	-91	-91.2	-91	-90.8	-91.2	-91	-90.8	-91.2	-91	-90.8	-91.2	-90.8
CPT-Value I	-141.928	-202.572	-197.609	-144.626	-188.083	-146.913	-114.705	-121.098	-217.679	-195.777	-142.503	-169.036
CPT-Value II	-203.317	-141.141	-126.713	-93.813	-116.525	-242.209	-76.324	-192.631	-199.803	-213.705	-234.258	-145.044
CPT-Value III	-194.721	-113.726	-206.196	-166.864	-143.935	-170.599	-146.714	-145.918	-123.658	-139.449	-198.754	-232.320
CPT-Value IV	-119.162	-118.353	-122.118	-117.290	-121.153	-165.928	-119.351	-164.971	-167.629	-163.491	-166.516	-164.318

CPT values are calculated by Tversky and Kahneman (1992) CPT-Parameters. The EPM values are not exactly equal in box IV since we round the premiums in order to generate integers.

Table A5.2: Decisions and Contracts

Number of contracts (complexity)	2	2	2	4	4	5	6	7	8	8	9	10	11	12
Order of decisions according to occurrence in the experiment	10	6	4	2	8	3	12	13	14	11	5	1	9	7
Design-box	2	1	3	1	4	2	1	3	1	4	2	3	1	2
Number of contracts that cover the potential loss of 2000	1	1	1	1	2	5	3	1	4	4	4	5	6	6
Number of contracts that cover the potential loss of 2000	2	0	1	2	2	2	3	4	4	4	4	5	5	6
Number of contracts with deductible 0	1	2	1	2	0	1	2	2	4	4	2	3	4	4
Number of contracts with deductible 10	0	0	1	0	0	2	1	3	1	4	4	3	3	4
Number of contracts with deductible 30	1	0	0	2	4	2	3	2	3	0	3	4	4	4
Contract predicted by minimax ignoring 2000	10	9	6	10	9	4	10	8	6	6	4	8	6	4
Contract predicted by minimax	1	3	5	4	4	4	4	2	1	1	4	4	1	4
Contract predicted by moderate minimax	10	9	6	4	4 or 10	4	4	8	6	1 or 6	4	10	6	4
Contract predicted by minimax ignoring deductible 10	1	3	5	4	4	4	4	2	1	2	4	5	1	4
Contract predicted by EPM	10	9	6	12	all	7	12	9	6	all*	4	10	11	7
Most frequently actual chosen contract	1	3	6	4	4	4	4	2	1	1	4	10	1	4
Expected contract by CPT assuming TK-values	1	3	5	4	4	7	4	2	1	2	4	10	7	7
Most frequently expected contract according to individual CPT	1	3	5	4	4	7	4	9	6	2	4	10	7	7

CPT values are calculated by Tversky and Kahneman (1992) CPT-Parameters. The EPM values are not exactly equal in box IV since we round the premiums in order to generate integers.

6 Conclusion

Rising health expenditure is a challenge for social insurance systems in many industrialized countries. This dissertation analyzes factors that all contribute to the trend of increasing health expenditure but work over different channels. Chapters 2 and 4 investigate negative health effects of common personal circumstances in industrialized societies. It is shown that the double burden of informal caregiving and full-time work deteriorates both, mental and physical health. The reason may lie in pressure imposed on caregivers that arises from two sides: (i) the pressure to provide informal care and (ii) the pressure to offer full-time work on the labor market to maintain financial stability. The conditions on labor markets also play a decisive roll when analyzing spillover effects of the fear of becoming unemployed in chapter 4. Both of these mechanisms do not only have in common that they are not easily detected as they are hidden consequences of different underlying conditions but also that there may be ways to prevent such adverse health effects once they are detected. With respect to the labor market, one may think of potential measures that may help to counteract adverse effects found in chapters 2 and 4. For example, more flexible work arrangements may have the potential to decrease worries about job security since threatening unemployment spells might be shortened. Further, it could improve possibilities to reconcile work and caregiving by allowing flexible arrangements. Reforms in the care sector that try to mitigate pressure on caregivers have already entered political debates in Germany during the final phase of writing chapter 2. The 'First Act to Strengthen Long-term Care' (Pflegestärkungsgesetz I) introduced short-time earnings-replacements to organize care and also increased benefits for care recipients. While these efforts may be a first step, they are presumably not capable of mitigating pressure for providers of informal long-term care. Hence, there may still be room for improvement with respect to long-term caregivers. However, benefits of intended reform outcomes must be carefully counted against their cost. Therefore, developing further cost intensive measures to prevent adverse health effects need to be well considered.

In Chapter 3, I investigate hidden factors for rising health expenditure from a different perspective using a stated choice method. The option value induced by technological progress is found to increase preferences for marginally effective treatments in terminal situations. This hidden factor is different from the aforementioned health effects as it cannot be prevented by political adjustments but calls for ex post measures. Certainly, priority setting or rationing may be possible solutions to contain such costs. However, not only do these measures have very bad reputation in society and are therefore politically not easily feasible[1] but they are connected to welfare losses as well. As long as the expenditure for such treatments reflects preferences, i.e. as long as society is willing and able to spend an increasing share of its GDP on such services, there is no need to intervene politically. The underlying utility of such treatments, even if the medical outcome is negligible, may be high in terminal situations. Therefore, analyzing preferences is crucial in order to carefully and deliberately apply direct measures of cost containment such as explicit rationing.

In chapter 5, the focus lies on analyzing hidden cost that arise due to inefficiencies on health insurance markets using a laboratory experiment. In contrast to treatment demand that may reflect preferences, inefficiencies on health insurance markets do certainly not reflect preferences of consumers. Hence, there is potential to reallocate resources in order to increase welfare. By encouraging competition on health insurance markets, inefficiencies can be tackled. Finding measures that acknowledge heterogeneity of preferences and the resulting complexity, which decreases the quality of health insurance choice, is crucial to help constructing more efficient health insurance markets. By controlling complexity, e.g. by employing preselection mechanisms, one may solve the trade-off problem between complexity and acknowledgment of heterogeneity in order to increase efficiency and to arrive at contracts that better reflect preferences of consumers.

[1] At least in an explicit sense.

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