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Christopher Karl Ludwig Schreckenberger

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Examination Committee

Chairperson: Prof. Dr. Klaus Prettner

Supervisor: Prof. Dr. Jörg Schiller

Co-Supervisor: Prof. Dr. Alfonso Sousa-Poza

Dean of Faculty: Prof. Dr. Karsten Hadwich

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List of Abbreviations

2SLS	Two-stage least squares
AHEAD	Asset and Health Dynamics
BMI	Body mass index
CEAR	Center for the Economic Analysis of Risk
CMS	Centers for Medicare & Medicaid Services
CompLTCI	Complementary long-term care insurance
DVfVW	Deutscher Verein für Versicherungswissenschaft
EGRIE	European Group of Risk and Insurance Economists
EuHEA	European Health Economics Association
FMM	Finite mixture model
GDP	Gross domestic product
GSOEP	German Socio-Economic Panel
HD	Huntington disease
HMO	Health Maintenance Organization
HRS	Health and Retirement Study
ICD	International Classification of Diseases
ISCO	International Standard Classification of Occupations
ISEI	International Socio-Economic Index of Occupational Status
IV	Instrumental variable
LPM	Linear probability model

LTC	Long-term care
LTCI	Long-term care insurance
MCBS	Medicare Current Beneficiary Survey
MRIC	Munich Risk and Insurance Center
NUTS	Nomenclature of territorial units for statistics
Obs.	Observations
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
PHAROS	Prospective Huntington At Risk Observational Study
PHI	Private health insurance
REVEAL	Risk Evaluation and Education for Alzheimer's Disease
SCREEN	Skin Cancer Research to Provide Evidence for Effectiveness of Screening in Northern Germany
SCS	Skin cancer screening
SD	Standard deviation
SHARE	Survey of Health, Ageing and Retirement in Europe
SHI	Statutory health insurance
SuppDI	Supplemental dental insurance
SuppHI	Supplemental health insurance
VPHI	Voluntary private health insurance

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1 General Introduction

A major policy concern in most OECD countries is the challenge of financing health and long-term care (LTC) expenditures. The public sector, including social insurance systems as well as governments, plays a key role in funding these expenses in most OECD countries. For instance, about 77% of total health expenditure in Germany in 2013 was publicly funded, mainly through contributions to the social security system. In addition to several factors, the aging of the population is likely to aggravate the financial burden on the public budget. Due to a rising life expectancy and decreasing birth rates, the average share of individuals aged 65 years and older in OECD countries is expected to nearly double from 15% in 2010 to about 27% in 2050, while the share of people in working age is expected to decline (OECD, 2015). In a social insurance system with a pay-as-you-go system, such as in Germany, population aging thus affects the financial equilibrium and leads to an intensified redistribution from people in working age to retirees (Breyer, Zweifel, & Kifmann, 2013). It is thus of particular interest to economically evaluate options that may help to alleviate the financial pressure on the public budget with respect to health and LTC expenditures. This thesis focuses on two specific options:

The first option refers to the arrangement of a health insurance and long-term care insurance (LTCI) system with respect to the mix of a public system and a private insurance market. By increasing the cost sharing or excluding coverage of specific services in the public system, the financial pressure on the public sector may be lowered. Simultaneously, individuals may be offered the opportunity to purchase voluntary private insurance coverage in order to reduce the coverage gaps in the public system. Policymakers in several OECD countries have considered and already implemented markets for voluntary private health insurance (VPHI) and private LTCI that coexist with a public system (e.g., Colombo, Llena-Nozal, Mercier, & Tjadens, 2011; OECD, 2004a).

In Germany, for instance, the majority of the population (about 88%) is covered in the statutory health insurance (SHI), while 12% have substitutive private health insurance (PHI) (Federal Ministry of Health, 2017). Even though SHI enrollees benefit from a relatively generous benefit package (Beske, Drabinski, & Golbach, 2005), copayments have been increased and some benefits have been excluded in the SHI in recent health reforms. As a result, markets for private supplemental health insurance (SuppHI) offered by PHI companies to reduce the coverage gaps in the German SHI have substantially increased in recent years (Grabka, 2014). Another example for a SuppHI market is the U.S. Medigap insurance market. Individuals covered in the Medicare program, which is a national social insurance program for the elderly in the U.S., face a substantial out-of-pocket expenditure risk and may purchase a Medigap insurance policy to reduce these coverage gaps (Fang, 2016). Moreover, private markets for voluntary private LTCI have evolved in some countries (e.g., U.S., Germany and France), even though these markets are still relatively small. In Germany, for instance, only 3.5% of individuals aged 40 years and older held a private LTCI policy that provides complementary insurance coverage for LTC expenditures not covered in the basic statutory LTCI in 2009 (Colombo et al., 2011).

While private insurance markets are an alternative funding source for health and LTC expenditures, these markets may suffer from inefficiencies due to the economic problem of asymmetric information and related selection effects. In contrast to public insurance systems, which are predominantly funded through income-related contributions or taxation (e.g., OECD, 2004a), premiums in private insurance markets are generally risk-based. Nevertheless, the problem of adverse selection may arise in private insurance markets with risk-based premiums if insurers are not able (or do not) sufficiently discriminate between different risk types. In the standard model of adverse selection (Rothschild & Stiglitz, 1976), individuals have residual private information on their risk type. In that case, individuals with a high risk will purchase more insurance coverage than low-risk individuals in a separating equilibrium. On the other hand, the theory of advantageous selection suggests that low-risk individuals are more likely to buy insurance coverage in a situation with multiple dimensions of private information. For instance, low-risk individuals may be more inclined to buy insurance coverage if they are more risk averse and if they simultaneously undertake more preventive effort to lower their risk exposure (de Meza & Webb, 2001). Even if both types of selection effects offset each other, they may lead to inefficiencies in an insurance market with respect to the coverage of at least part of the population (Finkelstein & McGarry, 2006). In addition to the potential problem of selection based on *ex-ante* private information, an *ex-post* risk-based selection may arise in markets with long-term contracts (e.g., private LTCI markets), if only the insurers can commit to the insurance contract. In such a situation, low-risk individuals who learn about their risk type over time may get incentives to cancel their contract if the amount of prepayments in the long-term contracts is insufficient to lock in low-risk types (Hendel &

Lizzeri, 2003). This would lead to a worsening of the remaining collective and a rise of the premiums for that collective (e.g., Brown & Finkelstein, 2009).

Another potential economic problem of asymmetric information in insurance markets is moral hazard that occurs when insurers are not able to observe the actions of individuals. This phenomenon generally refers to an unobservable change of individuals in their behavior as a response of holding insurance coverage. One specific form of that problem, called *ex-ante* moral hazard, arises when individuals decrease their preventive efforts prior to the loss occurrence due to insurance coverage (e.g., Zweifel & Eisen, 2012).[1] In a public health insurance system with comprehensive insurance coverage like the German SHI, enrollees may thus have low incentives to put effort into prevention (Breyer et al., 2013). One way to counteract this problem is to subsidize preventive health care as proposed by Arnott and Stiglitz (1986).

Hence, instead of shifting insurance coverage to a private insurance system, another option to alleviate the financial burden in a public health insurance system is to promote preventive health care, since this may reduce the overall health expenditures. An example is the implementation of the population-based skin cancer screening program (SCS) in the German health care system in 2008. An important aspect to evaluate in this context is whether promoted preventive measures are effective in reducing the morbidity and/or mortality of diseases like skin cancer and may thus lower the costs of care in a public health insurance system.

This dissertation contributes to the literature on the impact of these two individual options with a particular focus on the German LTCI and health insurance scheme. More specifically, three academic papers in this thesis analyze selection effects in markets for private LTCI and VPHI. The first paper, which is presented in Chapter 2, provides a literature review on the empirical work on asymmetric information and related selection effects in markets for private LTCI and in the U.S. market for Medigap insurance. Both types of insurance provide coverage for important out-of-pocket financial risks of the elderly population (e.g., Fang, 2016). A large body of recent empirical work has analyzed multidimensional private information and related selection effects particularly in these

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[1] Another type is *ex-post* moral hazard, which refers to an increased utilization of care services after the loss occurrence due to lower marginal costs of care (e.g., Pauly, 1968).

insurance markets. The review examines to what extent adverse and advantageous selection are present in these markets and to what extent several characteristics contribute to selection effects. Regarding the latter, a focus is on the role of private information that individuals have on their risk type, the role of the individual's risk preferences and of sociodemographic characteristics. The literature review points out potential directions for future research.

The third chapter provides an empirical analysis of selection effects in the market for complementary private LTCI in Germany based on a large dataset on more than 98,000 individuals from a German private insurance company. Even though the mandatory LTCI for SHI and PHI enrollees only provide partial insurance coverage, the demand for complementary private LTCI in addition to basic LTCI coverage is still rather low. Analyzing the selection behavior in this market is of interest for policy implications as selection effects may lead to market inefficiencies and thus contribute to the limited demand for this type of insurance coverage. Within a static framework, this chapter analyzes the coverage-risk correlation to provide insights whether selection effects in this insurance market exist. As premiums for this type of insurance are generally risk-based, but only dependent on few characteristics, this market is likely to suffer from selection effects. In a second step, potential drivers of selection effects are examined by testing whether characteristics (e.g., occupation) that are observable for the insurer, but not used for determining insurance premiums, are correlated with insurance coverage and the risk of needing LTC. The analysis in the static framework differentiates between the decision to buy complementary LTCI and to choose the amount of LTCI coverage. In a third step, this chapter focuses on the insurance uptake and lapse behavior in a dynamic framework and examines what characterizes the in- and outflow of the insured collective over time. While this analysis, in general, provides information on the stability of the insured collective over time, the findings on the lapse behavior, in particular, yield important insights into the potential problem of ex-post risk-based selection.

Chapter 4 addresses selection effects in the German market for supplemental dental insurance (SuppDI). Among different available types of SuppHI policies, this is the most popular one among SHI enrollees in Germany and showed the largest increase in recent years. Between 2004 and 2012, the share of SHI policyholders with a SuppDI rose from 5.6% to 16.6%. One possible explanation for this increasing demand is a change in the copayments for dental prostheses since 2005 to reduce the financial burden in the SHI (Grabka, 2014). Similar to the German market for complementary private LTCI, the risk classification in the market for SuppDI is mainly based only on few characteristics. Therefore, the shifting to a private insurance market for dental care services is prone to selection effects and may suffer from market inefficiencies. Using survey data from the Healthcare Monitor of the Bertelsmann Stiftung, the coverage-risk correlation is tested to analyze whether individuals have private information leading to selection effects in this market. In addition, several potential sources of selection are examined. The empirical findings on selection effects in this chapter provide insights that may be useful for policy implications concerning the shifting of dental insurance coverage from a public health care system to a VPHI market. This is of interest beyond the German health care system because dental benefits for adults are not fully covered by basic health insurance schemes in many OECD countries (Paris, Devaux, & Wei, 2010).

Another empirical paper, presented in chapter 5, shifts the focus of this thesis on the evaluation of promoting preventive health care by taking the implementation of the nationwide population-based SCS program in Germany as an example. Since the implementation of this program in 2008, the SHI offers a whole body examination for SHI enrollees at no charge every 2 years when they are at least 35 years old (Geller et al., 2010). By detecting skin cancer at an earlier stage, the primary aim of this program is to reduce mortality from malignant melanoma (Eisemann, Waldmann, Garbe, & Katalinic, 2015) and thus to reduce health care costs on skin cancer (Stang, Garbe, Autier, & Jöckel, 2016). Therefore, Chapter 5 examines the effect of this program on the number of hospital discharges following malignant skin neoplasm diagnosis and the malignant melanoma mortality rate per 100,000 inhabitants. The related research question is whether this program is effective with respect to these measures. To this end, panel data from the Eurostat database on subregions in 22 European countries, measured at the lowest nomenclature of territorial units for statistics (NUTS) level for 2000–2013, are used. By applying a fixed effects model to analyze the causal effect of the implementation of the German SCS program on the skin cancer diagnosis and the melanoma mortality rate, this chapter particularly contributes to the literature on assessing the effectiveness of SCS programs.

Finally, this dissertation ends with a summary of the key results in chapter 6.

2 Multidimensional Private Information and Selection Effects in Private Long-term Care Insurance Markets and the Medigap Insurance Market – A Review of the Empirical Evidence[2]

Abstract

This article reviews the empirical literature on asymmetric information and related selection effects in markets for private long-term care insurance and in the U.S. Medigap insurance market, which provides supplementary health insurance coverage for the elderly. The empirical work suggests that multidimensional private information are present in these insurance markets and lead to both adverse and advantageous selection. After providing an overview of the existence and the dominating type of selection in these markets, the evidence on several potential sources of selection is reviewed. With regards to the latter, the focus is on the role of the individual's private information about the risk type, of risk preferences and of sociodemographic characteristics. The review offers potential directions for future research concerning selection effects.

[2] The following chapter is a single authored manuscript by the candidate and yet unpublished.

2.1 Introduction

The share of the elderly population in OECD countries has risen over the last decades due to increasing life expectancies and fallen fertility rates. The percentage of people aged 65 years and older is expected to rise further from 15% in 2010 to 27% in 2050 on average across OECD countries (OECD, 2015). One of the most important financial risks that elderly people face are health care and LTC expenditure risks (e.g., Fang, 2016). Even though some public insurance programs, such as Medicare in the U.S. or statutory LTCI in Germany, provide basic insurance coverage for health or LTC expenses, people often still suffer from a substantial out-of-pocket risk (Bauer, Schiller, Schreckenberger, & Trautinger, 2017; Brown, Goda, & McGarry, 2012; Fang, 2016). Individuals may fill these coverage gaps by purchasing private LTCI coverage and supplementary health insurance coverage. Concerning the latter, elderly in the U.S., for instance, may buy Medigap insurance as a supplement to their health insurance coverage by Medicare.

One major concern in private health insurance and LTCI markets is asymmetric information and related selection effects. While private information of people about their risk type is expected to result in adverse selection of high-risk types into the insurance market (Rothschild & Stiglitz, 1976), multiple dimensions of private information may also lead to advantageous selection of low-risk types into the market (de Meza & Webb, 2001; Hemenway, 1990). Even though both selection effect may offset each other, market inefficiencies may still arise from the presence of multidimensional private information as at least part of the population is not able to get optimal insurance coverage at actuarially fair premiums (Finkelstein & McGarry, 2006). While a large empirical work has detected adverse selection in markets for acute health insurance (Cutler & Zeckhauser, 2000), an increasing number of empirical studies on markets for VPHI[3] and LTCI has taken multidimensional private information into account when testing for selection effects.

This paper reviews the empirical literature on selection effects into LTCI markets and the U.S. Medigap insurance with emphasis on multidimensional private information and the sources of selection. These markets are of particular interest since they provide voluntary insurance coverage for substantial out-of-pocket expenditure risks that the elderly

[3] VPHI comprises supplementary, complementary and duplicate health insurance as defined in OECD (2004b).

face. An overview of the evidence on the selection behavior may provide important insights into potential inefficiencies arising from selection effects in these markets. Moreover, the decision to buy insurance coverage for these risks are often made in older age. While only Medicare beneficiaries in the U.S. can buy Medigap policies, the average age of LTCI buyers in the U.S., for instance, is about 60 (Ko, 2016; LifePlans, 2017). Therefore, selection effects in these markets may be different compared to other VPHI markets.

2.1.1 Background

Theory suggests two different types of selection effects based on individual's private information, i.e., adverse and advantageous selection. Based on classical models of adverse selection (e.g., Rothschild & Stiglitz, 1976), individuals have one-dimensional private information about their risk type. In an equilibrium à la Rothschild and Stiglitz (1976), high-risk individuals choose more insurance coverage than low-risk individuals. The basic prediction of adverse selection is a positive correlation between insurance coverage and the risk of loss conditional on all characteristics used for risk classification (Chiappori & Salanié, 2000). Two equivalent parametric tests used in the literature are the regression of risk on insurance coverage[4] and a bivariate probit model (Cohen & Siegelman, 2010). Since the theory of moral hazard (e.g., Pauly, 1968; Shavell, 1979) also predicts a positive coverage-risk correlation, such a correlation is not a sufficient condition for adverse selection. Nevertheless, a positive coverage-risk correlation is quite robust in a perfectly competitive insurance market (Chiappori, Jullien, Salanié, & Salanié, 2006).

A negative coverage-risk correlation may point to a phenomenon called advantageous or propitious selection because low-risk individuals are more likely to purchase insurance coverage. Based on Hemenway (1990) and de Meza and Webb (2001), this phenomenon may arise when more risk averse individuals are more likely to buy insurance coverage and additionally undertake more effort into prevention, which lowers their risk of loss. Thus, in contrast to standard adverse selection models, individuals may make decisions on their insurance coverage based on multidimensional private information and are thus not only heterogeneous in their risk type, but also in their preferences for insurance coverage. In case that preferences for insurance coverage are negatively associated with the

[4] Alternatively, insurance coverage can be regressed on risk occurrence (Dionne, Gouriéroux, & Vanasse, 2001).

risk of loss, the insurance market may be advantageously selected (Cutler, Finkelstein, & McGarry, 2008; Fang & Wu, 2016). The market structure, however, plays a crucial role for the finding of a negative coverage-risk correlation even in the presence of multiple dimensions of private information. Consistent with Chiappori and Salanié (2013), Fang and Wu (2016) show that multidimensional private information and related selection effects do not lead to a negative coverage-risk correlation in a market equilibrium in perfectly competitive markets unless the loading factor in the insurance market is sufficiently large. In a monopolistic or, more generally, in an imperfectly competitive insurance market, however, a negative coverage-risk correlation may exist in equilibrium due to multidimensional private information.

Adverse and advantageous selection may not only arise from an informational disadvantage of insurance companies. Finkelstein and Poterba (2014) suggest that an insurance market may suffer from selection effects and the related market inefficiencies if observable characteristics significantly correlate with insurance demand and the risk of loss, but are not used for determining the insurance premium. They call these characteristics "unused observables". Possible explanations for the existence of unused observables are regulation and industry norms (Dardanoni & Li Donni, 2016). Furthermore, Kesternich and Schumacher (2014) show in a theoretical model that unused observables may also exist in an equilibrium when the insurance market is imperfectly competitive and the market entry is costly.[5]

In this review, thus, a characteristic can be considered as a source of advantageous selection under the following two conditions. First, it is not observable to the insurance company and/or not used for risk classification. Second, it is positively correlated with insurance coverage and negatively with the risk of loss (Fang, Keane, & Silverman, 2008; Finkelstein & McGarry, 2006). The theoretical model of de Meza and Webb (2001) suggests risk aversion as a key source of advantageous selection. A characteristic is a source of adverse selection if it is not used for pricing and if it is significantly associated with

[5] Further possible explanations for the presence of unused observables in insurance markets are discussed by Finkelstein and Poterba (2014) as well as Kesternich and Schumacher (2014).

insurance demand and the risk of loss in the same direction conditional on pricing. Standard models of asymmetric information predict that private information of individuals about their risk type is the key driver for adverse selection.

2.1.2 Previous Reviews and New Contribution

Some previous literature reviews consider the empirical literature on selection effects in health insurance and LTCI markets. In a review focusing on the market for acute health insurance in the U.S., Cutler and Zeckhauser (2000) report that 25 of 30 empirical studies find evidence consistent with adverse selection. This is supplemented by a review of Breyer, Bundorf, and Pauly (2012), who predominantly consider studies for the U.S. health insurance market divided by primary and supplementary insurance coverage. In these reviews, however, advantageous selection and its sources only play a minor role and selection effects in LTCI markets are not considered. In a closely related review, Kiil (2012) assesses the empirical literature on the determinants of VPHI in systems with universal health care systems in Europe, Australia and Israel. This review particularly examines the importance of socioeconomic characteristics, risk preferences and health-related factors. Concerning risk preferences, she concludes that the empirical evidence is still scarce and mixed. Even though this review considers to what extent the empirical evidence corresponds with theoretical predictions on selection effects, the focus is more on the role of different characteristics of privately VPHI enrollees instead of examining to what extent certain characteristics contribute to selection effects in different health insurance markets. Moreover, studies of the U.S. Medigap as well as LTCI markets are excluded. Brown and Finkelstein (2009) discuss several supply-side factors and demand-side factors that may contribute to the limited market size of the U.S. LTCI market, but only consider one study on asymmetric information.

Further previous reviews put more emphasis on the empirical literature on asymmetric information and selection effects in insurance markets without restricting to health insurance or LTCI. Cohen and Siegelman (2010) provide an extensive review of empirical studies on adverse selection in different insurance markets. Concerning health insurance, they, however, mostly rely on studies already reviewed by Cutler and Zeckhauser (2000), while they only include one study with respect to adverse selection in LTCI markets. Even though they discuss the existence of risk aversion and other factors that may lead to an offsetting of a positive coverage-risk correlation, their focus is rather on the existence and the variance of a positive coverage-risk correlation across different insurance markets than on sources of selection effects. The review of Chiappori and Salanié (2013) on asymmetric information in insurance markets puts more emphasis on the methodology in testing for asymmetric information and related difficulties than on the existence of selection effects and its sources. Chetty and Finkelstein (2013) shortly summarizes some evidence on selection markets with social insurance, but mostly rely on previous reviews with respect to findings in health insurance markets (e.g., Cutler & Zeckhauser, 2000).

This paper reviews the empirical work on selection effects in private LTCI markets and in the U.S. Medigap insurance market with a focus on the evidence regarding the presence and, in particular, the drivers of selection effects that arise from asymmetric information or unused observables. For these insurance markets, a growing number of studies examined the role of multiple dimensions of private information and related selection effects in recent years. The aim of this review is to examine in a first step whether and to what extent selection effects exist in private LTCI markets and in the Medigap insurance market. In a second step, this review analyzes what characteristics drive adverse and advantageous selection in these markets. By specifically focusing on the sources of selection effects in insurance markets, which cover important financial risks for the elderly, and by including more recent studies that are not addressed in previous reviews, this paper contributes to existing reviews on selection effects in insurance markets. This review can be used as a basis for future work on asymmetric information and related selection effects in insurance markets and for deriving policy implications.

The remainder of this paper is structured as follows. Section 2.2 describes the search strategy used to identify and to select the empirical studies for this review. Section 2.3 gives an overview of the identified studies and presents the results with respect to the research questions in this review. Section 2.4 concludes.

2.2 Methods

The search for empirical studies in this review is primarily based on an electronic search for literature in the databases EconLit and Business Source Premier (via EBSCO Host). The search terms that are used for this review are “((SU health insurance) OR (SU medical insurance) OR (SU Medigap) OR (SU long term care insurance)) AND ((AB asymmetric information) OR (AB private information) OR (AB adverse selection) OR (AB advantageous selection) OR (AB favorable selection) OR (AB selection effect*))”. The first component of the search terms refers to the type of insurance market. Using the field code SU (i.e., “Subject”) restricts the search for these terms to the subject heading field and thus enables a keyword search for subject terms that describe the content of an article. The second component aims at the identification of papers that analyzes information asymmetries and related selection effects. AB means that the search for the respective keywords is restricted to the abstracts. In addition to the main search in the databases, primarily reference lists of the identified literature were screened and, moreover, Google Scholar was used in order to get knowledge of further studies. The search is limited to relevant empirical studies in English or German published between 2005 and July 2017. The lower limit is set as empirical studies on multidimensional private information and advantageous selection in health insurance and LTCI markets are, to the best of the author’s knowledge, published after 2004. This should ensure that this review puts emphasis on studies that do not only analyze the existence of adverse selection, but also consider multidimensional private information and the related sources of selection.

The selection of studies and the insurance markets is based on the author’s subjective judgement of the studies concerning their relevance for answering the research questions. Table 2.1 presents criteria applied for including studies in this review. First, empirical studies published in peer-reviewed journals as well as working or discussion papers were eligible for inclusion given that they examine selection effects in LTCI markets or the U.S. Medigap markets. This implies that studies analyzing selection effects in other insurance markets, such as studies on health insurance policies with primary coverage or on other VPHI markets, are not primarily analyzed in this review. Purely theoretical articles were not included in this review.

It should be noted that this review does not claim to cover all empirical studies on selection effects in health insurance and LTCI markets. Nevertheless, the study search and study selection should ensure a good overview of the empirical literature on selection effects and especially on the sources of adverse and advantageous selection in private LTCI markets and in the Medigap insurance market.

Table 2.1: Inclusion Criteria

	Inclusion criteria
Publication type	Research articles in peer-reviewed journals; working or discussion papers
Focus of paper	Empirical analysis of private information and/or selection effects in insurance markets
Targeted market	Long-term care insurance market and/or the U.S. Medigap insurance market
Year of publication	2005-July 2017
Language	English and German

2.3 Results

2.3.1 Search Results

The literature search in the two databases yielded 432 search results in total. Of these, 16 articles remained after removing duplicates and excluding articles based on the selection criteria described in Section 2.2. After further searching for relevant papers primarily in reference lists of all identified articles, 9 studies were added. This results to 25 included studies on the targeted markets in this review. The majority of the included studies is published in a peer-reviewed journal ($n = 22$). The remaining articles are working papers ($n = 3$). 16 studies provide empirical evidence for private LTCI markets, while 11 studies analyzed the U.S. Medigap market.[6] Most of the studies are based on survey data with few exceptions (Bauer et al., 2017; Desmond, Rice, & Fox, 2006). Table 2.2 gives a summary of the selected empirical studies divided by the type of insurance market. In addition, some recent empirical evidence on selection effects in other VPHI markets, particularly from Europe and Australia, is used to consider the findings for LTCI and Medigap insurance in a broader context.

[6] Note, that 2 included studies (Dardanoni & Li Donni, 2016; Cutler et al., 2008) analyze both the U.S. LTCI market and the Medigap insurance market.

Table 2.2: Key Information about the Reviewed Studies on Selection Effects in Markets for Private Long-term Care Insurance and Medigap Insurance

Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
		LTCI	
Bauer et al. (2017)	Data from a German health insurance company (claims data from 2006–2014) combined with publicly available data (e.g., from the German Census and the Eurostat database); *N* = 98,305	In the aggregate, individuals holding a private complementary LTCI coverage are lower risk types than non-policyholders. Among complementary LTCI policyholders, those with more LTCI coverage are lower risks. The individual's occupational status, residential location and the holding of further supplementary health insurance policies are observable characteristics that are not used for pricing, but that incorporate information associated with insurance coverage and the risk of loss.	Socioeconomic status as a source of advantageous selection; mixed results for the role of holding of further supplementary health insurance policies
Braun, Kopecky, and Koreshkova (2017)	Health and Retirement Study (HRS) (1992–2012); number of observations not reported	Main findings of Finkelstein and McGarry (2006) with respect to the coverage-risk correlation are replicated using a quantitative model. Only individuals who are likely to be rejected by insurers have private information about their risk of a nursing home use at a 10-year horizon.	Not explicitly tested.
Brown et al. (2012)	Participants of the RAND American Life Panel aged 50 years and older (2011); *N* = 1,569	Controlling for observable characteristics, 27% of people who believe that they will need LTC in the future hold LTCI compared to 14% of people who do not expect to need care.	Self-assessment of LTC risk may contribute to adverse selection

Continued on next page

Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
Browne, and Zhou-Richter (2014)	Survey data from the German Socio-Economic Panel (GSOEP) with information on LTCI coverage from 1992 and information on the need for LTC from 1996–2006; *N* = 3,749 individuals	In the aggregate, the correlation between LTCI coverage and risk is positive, consistent with adverse selection as the dominating selection effect, but there are factors contributing to advantageous selection in addition to factors contributing to adverse selection.	Adverse selection: self-assessed financial readiness (major source), only minor role of further tested factors, such as self-assessed poor health; advantageous selection: preference for insurance and level of pessimism
Costa-Font, and Rovira-Forns (2008)	Computer-based survey of adult heads of households in Catalonia (1999); *N* = 383	Individuals with a higher perceived risk of disability are more likely to buy LTCI. In addition, some (e.g., individual health status), but not all proxies for the individual's risk occurrence, such as the self-assessed health, are positively correlated with the probability to buy LTCI.	Not explicitly tested, but evidence suggesting that private information about the individual's risk contributes to adverse selection
Courbage, and Rodaut (2008)	Sample of French individuals from the Survey of Health, Ageing, and Retirement in Europe (SHARE) (2007); *N* = 2,530	Individuals with higher LTC risk measured by alcohol consumption, body mass index and self-assessed health are more likely to buy private LTCI.	Not explicitly tested.
Finkelstein, and McGarry (2006)	Individual-level survey data from the Asset and Health Dynamics (AHEAD) cohort of the HRS (1995–2000); *N* = 5,072	Individuals have residual private information about their risk of nursing home use and this private information is positively associated with LTCI purchase. Controlling for risk classification, the correlation between ex-post risk occurrence and LTCI coverage is not significantly different from zero. Restricting the analysis to a more homogeneous subsample of healthier and wealthier individuals, the coverage-risk correlation is significantly negative. Multidimensional private information leads to an offsetting of adverse and advantageous selection.	Wealth and cautious health behavior (preventive health activities and seat belt use) as drivers for advantageous selection; self-assessment of nursing home risk as a source of adverse selection; education, race and number of children also contributing to adverse selection

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Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
Gan, Huang, and Mayer (2015)	Individual-level survey data from the AHEAD cohort of the HRS (1995–2000); N = 5,119	Individuals have private information about their risk. More risk averse individuals are less likely to go to a nursing home and more likely to buy LTCI.	Risk attitude measured by cautious health behaviors and wealth as a source of advantageous selection
Hendren (2013)	For the analysis on LTCI: HRS (1993–2008) and review of underwriting guidelines from major insurance companies; N = 31,262 observations (13,257 unique individuals)	In contrast to those individuals, who actually can buy insurance coverage, those, who are likely to be rejected by insurance companies, have a considerable amount of private information about their risk.	Not explicitly tested.
Ko (2016)	HRS (1998–2010); N = 5,105 for asymmetric information test and N = 19,283 family-year observations (4,183 families) for equilibrium analysis	Individuals have private information about the availability of informal care. Those who believe that their children will help in case of LTC are less likely to use a nursing home and less likely to hold LTCI coverage, i.e., substantial adverse selection based on private information about the availability of informal care.	Availability of informal care as a source of adverse selection
Oster, Shoulson, Quaid, and Dorsey (2010)	Data on people at risk for the Huntington disease (HD) from the Prospective Huntington At Risk Observational Study (PHAROS) (1999–2010) and data on individuals in the general population from the HRS (2000); N = 7,356	Individuals who are at about 50% risk for HD are more likely to hold LTCI than the general population with an approximately 0% chance for HD. The probability to hold LTCI is significantly higher for individuals who tested positive and know they carry the HD mutation compared to those who are at 50% risk for HD, but not tested, as well as compared to people who tested negative.	Not explicitly tested.

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Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
Su, and Spindler (2013)	For the analysis on LTCI: Same dataset as Finkelstein & McGarry (2006); *N* = 4,780	The null hypothesis of no asymmetric information can be rejected at the 10% significance level using a nonparametric test. Results suggest that individuals have some private information, which is related to their risk preferences.	Not explicitly tested.
Taylor et al. (2010)	The Piedmont Health Survey of the Elderly (1986–2006), for association of genetic information and nursing home use, *N* = 1,999; Risk Evaluation and Education for Alzheimer's Disease (REVEAL) Study with participants of the second trial for association between genetic information and LTCI purchase; *N* = 253	Among individuals who get genetic information about their future risk of Alzheimer's disease, those having an increased risk for that disease are 2.3 times more likely to increase their LTCI holdings after disclosure of this information.	Not explicitly tested.
Zick et al. (2005)	REVEAL study with participants at higher than average risk for developing the Alzheimer's disease (2000-2003); *N* = 148	Study participants with genetic information that they are at higher risk for the Alzheimer's disease are 5.76 times more likely to alter their LTCI coverage in the year after disclosure of genetic information than participants without genetic information. Results are not robust to sensitivity tests.	Not explicitly tested.
		Medigap	
Dardanoni, Forcina and, Li Donni (2016)	HRS (2002); *N* = 2,286	Individuals have private information leading to a positive coverage-risk correlation, but this correlation is heterogeneous across categories of risk and insurance coverage.	Education and cognitive abilities contribute to advantageous selection; mixed results for proxies for risk preferences

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Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
Dardanoni, and Li Donni (2012)	HRS (2002–2006; 2006 as reference point); N = 3,368	Substantial multidimensional residual private information leading to adverse and advantageous selection. There is adverse selection by individuals with both a high (low) propensity to purchase Medigap insurance coverage and to use inpatient care. Individuals with opposite attitudes to buy insurance coverage and to use inpatient care advantageously select into the Medigap market.	Key sources not explicitly tested.
Desmond et al. (2006)	Aggregated data from several sources on over 60 areas: Two large insurance companies, Centers for Medicare & Medicaid Services (CMS), Interstudy, U.S. Census, American Academy of Actuaries (1994–2000)	A rising Medicare HMO penetration rate of 10% leads to an increase of premiums for Medigap insurance policies by 0.9–2.5%, i.e., adverse selection into Medigap insurance market due to greater enrollment in Medicare HMO.	Not explicitly tested.
Fang et al. (2008)	Medicare Current Beneficiary Survey (MCBS) (2000–2001), N = 15,945 and HRS (2000–2002), N = 9,973	On average, Medigap policyholders have health expenditure of about \$4,000 less than non-policyholders; controlling for health, policyholders spend about \$1,900 more. Conditional on several factors contributing to advantageous selection (e.g., cognitive ability, income) health expenditures are positively correlated with Medigap insurance coverage.	Sources of advantageous selection: cognitive ability (key source), income, education, expectations on longevity and financial planning horizon; risk aversion is not a main source of advantageous selection

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Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
Hu, Munkin, and Trivedi (2015)	MCBS (2003–2005); *N* = 2,309 observations	Medigap enrollees with prescription drug coverage are lower risk types than those without prescription drug coverage. For instance, the average treatment effect ($1,132) is larger than the average treatment effect of the treated ($858). As the latter represents the treatment effect of those who actually hold prescription drug coverage, while the first is the treatment effect of a randomly selected individual, the authors suggest that this provides evidence of advantageous selection.	Not explicitly tested.
Keane, and Stavrunova (2016)	MCBS (2000–2001), *N* = 14,129 and HRS (2002), *N* = 1,671	Conditional on covariates used for pricing, Medigap insurance coverage correlates negatively with risk (i.e., advantageous selection as dominating selection effect). After additionally controlling for several sources of selection (e.g., cognitive ability), there is only weak adverse selection; a rise in expenditure risk by one standard deviation is associated with a rise in the probability of purchasing Medigap insurance by 5.5 percentage points. Findings indicate that selection on unobserved health is less important.	Sources of advantageous selection: cognitive ability and income (key sources), education, expectations on longevity, financial planning horizon; only minor role of risk aversion; indicators for blacks and Hispanics (i.e., race) as important source of adverse selection
Li, and Trivedi (2016)	MCBS (2003–2004); *N* = 7,664 observations (5,725 unique individuals)	Concerning prescription drug expenditures, both adverse and advantageous selection exist in Medicare supplemental plans including Medigap; for instance, there is adverse selection into Medigap plans relative to basic Medicare fee-for-service plans only, but advantageous selection into Medigap with prescription drug coverage relative to Medigap without drug coverage.	Not explicitly tested.
Munkin, and Trivedi (2010)	MCBS (2003–2005) with additional data from the Area Resource File and the State County File; *N* = 7,273	There is adverse selection into supplemental plans with prescription drug coverage, particular for the higher expenditure latent type; no disaggregation for different types of supplemental plans that offer prescription drug coverage to isolate selection effects specifically in Medigap plans.	Not explicitly tested.

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Author (year)	Data	Key results concerning private information and selection effects	Identified sources of selection
Zimmer (2012)	Medical Expenditure Panel Survey (2000–2005); *N* = 15,787	Overall, holding supplemental insurance coverage is positively associated with health care expenditure. But consistent with advantageous selection, individuals with supplemental insurance are, on average, healthier. Individuals with access to employer-sponsored supplemental insurance have lower health care expenditure. People do not select into supplemental insurance based on their risk preferences. Expenditures on prescription drugs do not considerably differ between individuals with and without supplemental insurance coverage.	Some socioeconomic characteristics contribute to advantageous selection; only minor role of risk aversion as a source of selection
		Medigap and LTCI	
Cutler et al. (2008)	AHEAD sample of the HRS for analyzing the market for LTCI (1995–2002), *N* = 6,401 and for Medigap (1995), *N* = 6,383	More risk averse (proxied by five measures of behavior, such as smoking) individuals are more likely to hold five types of insurance policies including Medigap and LTCI. Some proxies for risk aversion (e.g., seat belt use) are negatively associated with nursing home use, but not systematically associated with health care costs covered by Medigap policies.	Risk preferences as a source of advantageous selection in LTCI markets, but not in the Medigap market
Dardanoni, and Li Donni (2016)	LTCI: AHEAD cohort of the HRS (1995–2000); restricted sample of individuals in the top quartile of the wealth and income distribution and without health conditions that could lead to a rejection by insurers; *N* = 1,491	Conditional on risk classification, individuals are heterogeneous with respect to cautiousness. Cautious individuals are 2.5 times less likely to enter a nursing home, but four times more likely to buy LTCI. The welfare loss of unpriced heterogeneity is about 7.5–10% of total insurance coverage costs.	Cautiousness as a source of advantageous selection
	Medigap: HRS (1994–2010); *N* = 5,432	Conditional on risk classification, there is multidimensional heterogeneity leading to both adverse and advantageous selection. The welfare loss of not pricing on residual heterogeneity is about 14–28% of total insurance coverage costs.	No specific source of selection identified.

Notes: The number of observations within the studies varies due to different estimation models and missing values for some variables. In this table, the maximum number of observations used in the study is reported.

2.3.2 Existence of Selection Effects in Insurance Markets

2.3.2.1 Long-term Care Insurance Markets

LTCI generally provides financial compensation for LTC services in an institution, such as a nursing home, or at the care recipient's home when individuals suffer from physical and/or cognitive impairment in performing routine activities of daily living, such as bathing, eating and dressing (e.g., Brown & Finkelstein, 2009; Courbage & Roudaut, 2008). In this review, the included studies examine existing private LTCI insurance markets in the U.S., France and Germany.[7] With regards to the population coverage, these are one of the largest markets even though the demand is still rather low. For instance, only 5% of the U.S. population aged 40 years and older held a private LTCI in 2010.[8] Typically, private LTCI markets coexist with a public LTC system. For instance, in the U.S., private LTCI policies offer coverage for individuals that are not eligible for Medicaid, which is the public insurance program for the indigent. In other OECD countries, such as Germany and France, private LTCI provides complementary LTCI coverage in addition to basic public coverage for LTC services (Colombo et al., 2011). In contrast to the evidence on many health insurance markets, the empirical literature on LTCI markets suggests that multidimensional private information play an important role for this insurance type and lead to both adverse selection and advantageous selection.

Most of the existing studies analyze the private LTCI market in the U.S. based on data from the Health and Retirement Study (HRS). In a seminal paper, Finkelstein and McGarry (2006) provide evidence of multiple dimensions of private information in this insurance market. In a first step, they test for asymmetric information directly by examining the individual's subjective assessment of the probability of entering a nursing home. They control for the risk classification by insurance companies including the individual's age and health status. In case of poor health conditions, applicants may even be rejected

7 It should be noted that in some countries (e.g., U.S. and France), people may have private LTCI coverage by individual contracts or by group insurance policies, which are typically offered by employers (Colombo et al., 2011).

8 In France, about 15% of the population held a private LTCI policy in 2010, while only about 3.5% of the German population aged 40 years and older held a private complementary LTCI policy (Colombo et al., 2011).

by insurance companies.[9] They find that individuals have residual private information about their risk of becoming a nursing case and that this private information is positively correlated with the holding of LTCI as proposed by standard adverse selection models. Applying the bivariate probit model based on Chiappori and Salanié (2000) in a second step, they do not find evidence that individuals with a higher risk experience are more likely to buy LTCI coverage after controlling for the risk classification. Restricting the analysis to a more homogeneous sample of individuals, who are in the top quartile of the wealth distribution and who do not have any health conditions that might lead to a rejection by insurers, they even find a significantly negative coverage-risk correlation. As an explanation for these seemingly conflicting results, they suggest that individuals also have private information about factors other than the risk type and that this may lead to advantageous selection and an offsetting of adverse selection in the aggregate. Their results provide suggestive evidence that cautiousness and wealth are factors that contribute to advantageous selection.

Some more recent studies propose alternative econometric approaches to test for asymmetric information and apply their approach to the same dataset as Finkelstein and McGarry (2006) without using information of the individuals' self-assessed probability to enter a nursing home. Su and Spindler (2013), for instance, show that asymmetric information exist in the U.S. LTCI market by applying a nonparametric test. Their findings suggest that individuals have some sort of private information that is related to the risk attitude as opposed to risk occurrence. Using a finite mixture model (FMM), Dardanoni and Li Donni (2016) as well as Gan et al. (2015) find evidence of multidimensional private information in this insurance market. They identify two types of individuals that substantially differ in their insurance demand and risk occurrence as well as in their cautiousness. Dardanoni and Li Donni (2016), for instance, show that more cautious individuals are four times more likely to purchase LTCI, but about 2.5 times less likely to enter a nursing home than more reckless individuals. In sum, these studies support the main results of Finkelstein and McGarry (2006).

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9 In the U.S., insurance companies offering private LTCI apply medical underwriting and may reject applicants if they have health conditions that make them more likely to become a nursing case, such as restrictions in activities of daily living - and/or if they are aged 80 years and older and are thus likely to be too costly for insurance companies (Hendren, 2013). Braun et al. (2017) estimate that 36% of individuals aged 55–66 would be rejected in the U.S. LTCI market due to medical underwriting.

Braun et al. (2017) develop a quantitative optimal contracting model of the U.S. LTCI market to analyze the empirical relevance of several demand-side and supply-side frictions. Calibrating their model based on HRS data, they are able to reproduce the main findings of Finkelstein and McGarry (2006) with respect to the evidence of asymmetric information and with respect to the correlation between LTCI coverage and nursing home entry. As their model is based, however, on the assumption that individuals only have one-dimensional private information, their results propose alternative explanations for a small positive or even a negative coverage-risk correlation. Their model, for instance, suggests that the correlation between the holding of LTCI coverage and loss occurrence is positive, but small since low- and high-risk types do not differ in the LTCI uptake rate within most groups of individuals that are identical for an insurance company.

In countries other than the U.S., the empirical literature on selection effects in LTCI markets is rather sparse and mixed. In Germany, premiums for private complementary LTCI policies are based on the age at the date of the insurance uptake and, up to and including December 2012, on gender. Similar to the U.S. LTCI market, insurance companies may reject applicants based on medical underwriting. Consistent with the evidence on the U.S. LTCI market, studies on selection effects into private LTCI in Germany show that both adverse and advantageous selection are present. Browne and Zhou-Richter (2014) find that adverse selection is the dominating selection effect in the German LTCI market. As they additionally identify some sources of advantageous selection, such as the individuals' level of pessimism, their findings indicate that selection effects are based on multidimensional private information. The latter is supported by Bauer et al. (2017)[10], who find that individuals with a complementary LTCI are lower risks than non-policyholders and that those policyholders with higher LTCI coverage are lower risks than those with lower LTCI coverage. In contrast to Browne and Zhou-Richter (2014), this finding suggests that the LTCI is predominantly advantageously selected. They identify the occupation, residential location and holding of further supplementary health insurance policies as unused observables since these factors include information that are associated with LTCI coverage and the risk of loss, but are not used by the insurer for pricing. One possible explanation for the differences in the findings between both studies are differences in the data sources. While Browne and Zhou-Richter (2014) use survey data from

[10] This study is presented in detail in chapter 3 of this dissertation.

the German Socio-Economic Panel (GSOEP) that includes information of individuals of the SHI and the substitutive PHI, Bauer et al. (2017) use data from a German PHI company only on enrollees of the substitutive PHI, which is not representative for the whole German population.[11] Moreover, the different time periods may explain differences in the empirical findings.

With regards to the French market for private LTCI, Courbage and Roudaut (2008) find some suggestive evidence that adverse selection is present in this market as some indicators for LTC risk, such as the body mass index, are positively correlated with LTCI coverage controlling for age as a proxy for the pricing of LTCI policies. However, they conclude that this finding is to be considered with caution due to limitations in the data, such as regarding the insurance product's characteristics. Costa-Font and Rovira-Forns (2008) analyze determinants of the ex-ante demand for LTCI in a time of inexistence of LTCI policies in Spain using a representative sample of Catalonia. Similar to the evidence for the French LTCI market, they also find some evidence in favor of adverse selection. Consistent with findings of Finkelstein and McGarry (2006), they show that individuals with higher perceived LTC risks are associated with a higher probability to purchase LTCI. Moreover, some measures which are related with an individual's LTC risk, such as the health status, are also positively associated with the demand on LTCI.

It should be noted that LTCI policies, such as in the U.S. and in Germany are typically long-term term contracts that are guaranteed renewable (Pauly, Kunreuther, & Hirth, 1995). In a situation with a lack of consumer commitment, i.e., policyholders may let their policy lapse, and with policyholders that learn about their risk of loss over time, the risk pool may worsen over time if the front-loading in these policies is insufficient to lock-in low-risk individuals (Hendel & Lizzeri, 2003). Thus, LTCI markets may not only suffer from selections effects into the market, but also from an ex-post selection of low-risk types out of LTCI policies.[12] While there is some evidence of such ex-post risk-based

[11] In Germany, only about 12% of the population is covered by the substitutive PHI, while about 88% is covered by the SHI (Federal Ministry of Health, 2017). Only dependent workers or employees with an income above a certain income threshold, civil servants and self-employed individuals may opt for the German substitutive PHI.

[12] *Ex-post* in this context means after the signing of the insurance contract.

selection (Finkelstein, McGarry, & Sufi, 2005), some more recent studies provide evidence suggesting that LTCI policy lapses are rather an issue of financial problems (Bauer et al., 2017; Konetzka & Luo, 2011).

2.3.2.2 Medigap Insurance Market

The public insurance program Medicare in the U.S. provides primary health insurance coverage for most elderly aged 65 and older as well as for disabled individuals. Traditional fee-for-service Medicare plans provide insurance coverage for hospital care (Part A) and outpatient medical care services (Part B). However, enrollees of these plans bear a considerable financial risk due to out-of-pocket expenses on health care including copayments, deductibles and uncovered benefits. They may buy a Medigap plan as a supplemental insurance policy from PHI companies to fill these coverage gaps. Relative to the U.S. market for private LTCI, the Medigap insurance market is highly regulated. First, in most states, insurance companies can sell only ten standardized policies with similar benefits. Second, ex-ante premium differentiation is limited since pricing is mainly based on age, gender, place of residence and the smoking status. In addition, there is no medical underwriting at least in the 6-month open enrolment period, which starts after individuals are at least 65 years old and are enrollees of Medicare Part B. This regulation makes this market prone for selection effects (Fang et al., 2008).

As reviewed by Breyer et al. (2012), the evidence on selection effects of Medicare enrollees into the Medigap market based on studies published before 2005 is mixed. Recent empirical studies on selection of Medicare beneficiaries into the Medigap insurance market provide evidence that multidimensional private information may explain these ambiguous results. In a widely noted paper, Fang et al. (2008) find that Medicare beneficiaries with Medigap insurance spend, on average, about $4,000 less than individuals without that SuppHI coverage, but about $1,900 more after controlling for health indicators. While the first finding provides evidence of multidimensional private information, the latter is consistent with ex-post moral hazard. Taken both results together indirectly points to advantageous selection in the aggregate, i.e., elderly with better health are more likely to hold a Medigap policy. After gradually adding several potential sources of advantageous selection to their regression of Medigap coverage on expected medical expenditure and pricing characteristics they find that the coverage-risk correlation turns positive as proposed by standard adverse selection models.

Several more recent studies on the Medigap market corroborate the key findings of Fang et al. (2008) concerning selection effects. A closely related paper by Keane and Stavrunova (2016) extends the work of Fang et al. (2008) in several ways, especially by using a simultaneous equations model for jointly analyzing selection and moral hazard effects. Their model enables them to account for endogeneity of insurance status when examining the extent of selection effects. Using the same database as Fang et al. (2008), their results are similar to those of Fang et al. (2008) concerning multidimensional private information, the extent of selection effects as well as the sources of selection in this market.[13] However, using an extended set of potential sources of selection, they only find a weak adverse selection effect that is smaller by one third compared to that measured by Fang et al. (2008). Specifically, they find that a rise in health care expenditure risk by one standard deviation (i.e., $12,700) is associated with an increased probability of holding Medigap insurance by 5.5 percentage points. Among a huge set of factors, both studies particularly identify the individual's cognitive ability and income, but not the risk attitude as a key driver for advantageous selection. Based on survey data from the Medical Expenditure Survey Data, Zimmer (2012) separately analyze Medigap policies from employer-sponsored supplemental insurance coverage for Medicare beneficiaries. He also finds evidence suggesting that Medicare beneficiaries with better health advantageously select into supplemental insurance coverage. However, in contrast to the findings of Fang et al. (2008), he shows a positive relationship between health care expenditure and Medigap coverage unconditional on health and further covariates, which may at least to some extent be explained by differences in the data sources.

Dardanoni et al. (2016) propose a multivariate ordered logit regression model for testing for asymmetric information in insurance markets and apply it on the U.S. Medigap insurance market. Their approach extends the standard bivariate probit model based on Chiappori and Salanié (2000) by considering ordered categorical dependent variables instead of binary dependent variables and by considering several risk measures simultaneously. Using doctor visits and hospital stays as risk measures, they do not only find evidence of asymmetric information in this market, but a positive correlation between

[13] Keane and Stavrunova (2016) additionally find evidence of advantageous selection on health that is unobserved to the econometrician, even conditional on the entire set of potential sources of advantageous selection. However, their results indicate that the unobserved components of health are less important with respect to the extent of adverse selection in this market.

Medigap insurance coverage and these risk measures, which is not homogenous across categories of risk and insurance coverage. Their findings imply that the coverage-risk correlation depends on how risk and insurance coverage are classified into high and low. In line with other studies on the Medigap market (e.g., Fang et al., 2008), their results additionally reveal that individuals have multidimensional private information (e.g., on cognitive abilities) leading to advantageous selection in this market.

Using HRS data, Dardanoni and Li Donni (2012) examine ex-post moral hazard and selection effects on inpatient care. They apply a recursive bivariate probit model and a discrete multivariate FMM to disentangle selection from moral hazard. Based on the idea that a finite number of types that are heterogeneous in the purchase of insurance coverage and in the utilization of medical care can be identified conditional on the pricing characteristics, the latter model aims at understanding selection effects under multidimensional private information. They identify four types that represent residual heterogeneity and provide evidence of substantial multidimensional private information leading to adverse and advantageous selection in this market. For instance, they find, conditional on risk classification, that some individuals are more likely to buy Medigap insurance coverage and to use inpatient care (consistent with *adverse* selection), while some individuals have a high preference for insurance, but a low inpatient care use (consistent with *advantageous* selection). Their findings suggest that low-risk types suffer from substantial cross-subsidization of high-risk types. Similar, Dardanoni and Li Donni (2016) identify five types of individuals that have expected medical costs independent of insurance coverage within these types, but that differ substantially in the expected medical costs and in the Medigap insurance coverage conditional on the insurer's risk classification across the types. There is no clear order of the types in terms of both risk of loss and insurance coverage. For instance, one high-risk type has a relatively high probability to buy LTCI compared to low-risk types, while the opposite holds for another type of high-risk individuals. Their findings of the large heterogeneity of these types indicate the existence of multidimensional private information and the presence of both types of selection. They estimate that the lack of premium differentiation across these types and the associated implicit cross-subsidization between high- and low-risks is about 25% of total insurance coverage costs.

As an alternative source of supplemental insurance coverage for the elderly in the U.S., individuals may choose to enrol in Medicare managed plans, such as Health Maintenance Organizations (HMO), which are also called Medicare Advantage plans or Medigap Part C. In these plans, enrollees have lower deductibles and co-payments as well as more benefits than in traditional Medicare, but are restricted to receive benefits only from the provider network of the managed care plan (Fang, 2016). Using aggregated data, Desmond et al. (2006) analyze the effect of Medicare HMO enrolment on premiums in the Medigap insurance market. Their results indicate that an increased Medicare HMO penetration rate is associated with a moderate rise of Medigap premiums. They conclude that Medicare HMO plans cause an adverse selection into the Medigap insurance market. A possible explanation for this result is that SuppHI coverage for Medicare enrollees through managed care plans is less attractive for sicker individuals due to the restrictions in the choice of health care providers.

Traditional Medicare plans do not provide insurance coverage for prescription drugs. Before the introduction of Medicare Part D in 2006, which provides optional prescription drugs coverage for Medicare beneficiaries, three out of ten standardized Medigap plans offered optional drug coverage (Hu et al., 2015). While anecdotal evidence suggests that drug coverage appears to be heavily adversely selected (Breyer et al., 2012), recent studies use data from the Medicare Current Beneficiary Survey to examine ex-post moral hazard and selection effects with respect to prescription drug coverage offered in some Medigap plans before 2006. By applying econometric approaches (e.g., an extended two-part model) that incorporate instrumental variables, these studies estimate moral hazard effects as treatment effects while accounting for unobserved selection effects into supplemental plans.

Munkin and Trivedi (2010) find evidence in favor of adverse selection of Medicare beneficiaries into supplemental prescription drug coverage, particularly for the group of individuals with higher average drug expenditures. They consider, however, drug coverage at an aggregated level without allowing for differences between prescription drug coverage through a Medigap plan and other sources. Li and Trivedi (2016) conduct a more disaggregated analysis and distinguish between employer-sponsored insurance plans, Medicare managed care plans and Medigap plans with and without drug coverage. Focusing their analysis on prescription drug expenditures, their findings suggest that both adverse and advantageous selection into supplemental plans are present. For instance, they find evidence of adverse selection for Medigap plans relative to the choice of Medicare without supplemental insurance coverage, but advantageous selection for Medigap plans with prescription drug coverage relative to Medigap plans without drug coverage. In another study, Hu et al. (2015) provide several findings that are in favor for advantageous selection. For instance, they show that the incentive effect of prescription drug coverage measured with the average treatment effect is more than $1,132, while the observed difference in the expenditure on prescription drugs between individuals with and without such prescription drug coverage is only $337. As the latter includes both moral hazard and selection effects, the authors conclude that this indicates the presence of advantageous selection. In sum, the findings of these studies on prescription drug coverage indicate that both adverse and advantageous selection are present, which may be explained by multidimensional private information. However, these studies do not explicitly examine sources of selection.

It should be noted that particularly recent studies on the Medigap market take the problem of disentangling selection effects from incentive or treatment effects in their econometric approach into account (Dardanoni & Li Donni, 2012; Hu et al., 2015; Keane & Stavrunova, 2016). Thus, the evidence on multidimensional private information and related selection effects in this insurance market based on the studies included in this review is less likely to be biased by any moral hazard effects.[14] Moreover, it seems to be less likely that a negative coverage-risk correlation results from denials of high-risk individuals, since rejections of enrollees are only possible after the 6-month open enrollment period. Fang et al. (2008) show and discuss that advantageous selection in this market is rather driven by the choice of consumers themselves than by cream skimming activities by insurance companies. Nevertheless, there is still need for further research on this issue (Fang, 2016).

The empirical evidence of multidimensional private information and the existence of both adverse and advantageous selection in the Medigap insurance market is consistent with findings for other VPHI markets that coexist with public health care systems. For different European VPHI markets, there is some evidence of adverse selection (Franc,

[14] The different approaches are not discussed in more detail in this review. See Cohen and Siegelman (2010) and Dionne (2013) for a discussion of disentangling moral hazard effects from selection effects.

Perronnin, & Pierre, 2010; Lange, Schiller, & Steinorth, 2017; Olivella & Vera-Hernández, 2013; Schokkaert, Van Ourti, De Graeve, Lecluyse, & Van de Voorde, 2010). Using data from the Survey of Health, Ageing, and Retirement in Europe (SHARE) on people aged 50 and older in eleven European countries, Paccagnella, Rebba, and Weber (2013), for instance, find that those with low physical health are more likely to hold VPHI in Denmark, Netherlands, Switzerland and Austria. Even though their focus is not on testing for asymmetric information, they conclude that this might point to adverse selection in these countries. Several other studies provide evidence indicating that advantageous selection exist in European VPHI markets (e.g., Bolhaar, Lindeboom, & van der Klaauw, 2012; Schmitz, 2011) and in the Australian market for private duplicate health insurance (e.g., Buchmueller, Fiebig, Jones, & Savage, 2013; Doiron, Jones, & Savage, 2008). Based on SHARE data, Bolin, Hedblom, Lindgren, and Lindgren (2010) even find a negative association between risk and VPHI coverage in several European countries for individuals at the age of 50 years and older. These findings support the results for the Medigap insurance market even though VPHI policies in some markets (e.g., Australia) aim at improving the quality and service of health care as well as the access to health care rather than at reducing financial risks. Moreover, it should be noted that, compared to the Medigap insurance market, those VPHI markets in Europe and Australia in general do not focus on the elderly population.

2.3.3 Sources of Selection

2.3.3.1 Risk Type

Theory proposes that private information of individuals about their expected risk of loss is the most important source of adverse selection (e.g., Rothschild & Stiglitz, 1976). Findings of a positive coverage-risk correlation conditional on the insurer's risk classification may be explained by residual private information of individuals about their risk type given that moral hazard is sufficiently controlled for. Consistent with ambiguous effects of self-reported health measures on holding VPHI (see Kiil, 2012 for a review), the evidence based on explicit tests for this type of private information in private LTCI markets is mixed. While Courbage and Roudaut (2008), for instance, find that individuals with bad self-assessed health are more likely to purchase private LTCI in France, some studies provide direct evidence suggesting that individuals with higher self-perceived risk are more likely to purchase LTCI coverage (Brown et al., 2012; Costa-Font & Rovira-Forns, 2008; Finkelstein & McGarry, 2006).[15] Browne and Zhou-Richter (2014), however, find that individuals with worse self-assessed health are more likely to have a higher risk of becoming a nursing case, but not more likely to buy LTCI relative to individuals with a better self-assessed health. The latter is in line with many findings in markets for VPHI (Kiil, 2012) and, following Zhou-Richter, Browne, and Gründl (2010), may be explained by the unawareness of some individuals with bad health with respect to their LTC risk. In addition, it may also be difficult for some individuals to predict their future LTC risk adequately and thus to make optimal decisions on LTCI coverage.

Some recent studies suggest that private information about risk among those individuals, who are unlikely to be rejected by insurers and are thus actually able to buy LTCI, is not a key source of adverse selection. Hendren (2013) proposes that the absence of a positive correlation between insurance coverage and risk occurrence, as shown by Finkelstein and McGarry (2006), may be explained by rejections of applicants. Analyzing the U.S. LTCI market, Hendren (2013) as well as Braun et al. (2017) find that individuals, who are likely to be offered LTCI policies, do not have significant private information conditional on criteria used for risk classification, while people that would be rejected by insurance companies have a relatively larger and significant amount of private information. As the latter type of individuals are higher risk types, the possibility of rejections by insurance companies may prevent adverse selection and thus a positive correlation between insurance coverage and risk occurrence. Based on the observation that the LTCI uptake rate declines with observable frailty, Braun et al. (2017) show that the coverage-risk correlation may even be negative in a setting with one-dimensional private information if the researcher does not sufficiently control for the information set of an insurer and hence for possible rejections of high-risk individuals. In line with these findings, Ko (2016) provides evidence that, among people who are less likely to be rejected in the U.S. LTCI market, the individual's belief of entering a nursing home is not significantly associated with actual nursing home use conditional on pricing characteristics and beliefs

[15] Brown et al. (2012) note some potential limitations concerning their findings and its generalizability as, for instance, their results may be biased by reversed causality or sample selection. Even though they find a strong positive relationship between the expectation about the need for LTC and LTCI coverage in the U.S. after controlling for some observable sociodemographic characteristics, they may not sufficiently control for risk classification.

about the availability of informal care. It should be noted, however, that the finding of Finkelstein and McGarry (2006) of a negative correlation between LTCI coverage and nursing home use among a more homogeneous subsample of wealthier and healthier individuals is unlikely to be explained by rejections.

While some evidence casts doubt that some individuals have private information their risk type, genetic tests are increasingly available and may provide individuals additional private information about their risk of suffering from a disease. In the U.S., the Genetic Information Nondiscrimination Act of 2008 outlaws health insurance companies to use genetic information, but does not explicitly consider other insurance markets including LTCI (Taylor et al., 2010). Some studies examine genetic testing on specific diseases and the related selection behavior in the U.S. LTCI market and provide evidence suggesting that genetic testing may cause or exacerbate adverse selection. Zick et al. (2005), for instance, find that individuals who receive genetic information that they are at higher risk for the Alzheimer’s disease are more likely to alter their LTCI coverage than those without disclosure of genetic information. Taylor et al. (2010) provide evidence that confirm these results and show that individuals with a higher risk of the Alzheimer’s disease based on genetic testing are more likely to enter a nursing home. Major limitations in these studies concerning LTCI purchase are the small sample size and the restriction to participants who are higher than average risk types for the Alzheimer’s disease. Oster et al. (2010) find that individuals who know that they carry the Huntington disease (HD) mutation based on genetic testing are significantly more likely to hold LTCI coverage relative to the general population with an approximately chance of 0% to have HD. Among the individuals at risk for HD, the probability to hold LTCI is significantly higher for those who find out that they carry the HD genetic mutation based on genetic testing compared to those with negative test results for carrying this genetic mutation. The authors conclude that an increased availability of genetic information may lead to increasing private information for individuals about their risk type and thus to an exacerbation of adverse selection and related market inefficiencies.

2.3.3.2 Risk Preferences

While the evidence on the association of risk preferences and the demand for insurance coverage in VPHI markets other than the Medigap market is sparse (Kiil, 2012), several studies on LTCI markets and the Medigap insurance market examine the role of risk preferences as it is proposed to explain advantageous selection (e.g., de Meza & Webb, 2001). In the literature, there is no standard measure used for risk attitude (Anderson & Mellor, 2008). Thus, there is a wide range of proxies used for risk preferences in the studies on LTCI markets and on the Medigap insurance market including *self-reported risk attitudes* (Costa-Font & Rovira-Forns, 2008; Zimmer, 2012), individual's *cautiousness* (Browne & Zhou-Richter, 2014; Cutler et al., 2008; Dardanoni et al., 2016; Dardanoni & Li Donni, 2016; Finkelstein & McGarry, 2006; Gan et al., 2015; Zimmer, 2012), the individual's *preference for insurance* measured by the ownership of other types of insurance (Bauer et al., 2017; Browne & Zhou-Richter, 2014), a measure based on individual's *choices over hypothetical income gambles* (Fang et al., 2008; Keane & Stavrunova, 2016) as well as the *share of portfolio invested in safer assets* (Dardanoni et al., 2016; Dardanoni & Li Donni, 2016).

Particularly the latter two measures capture financial risk aversion. This may be different from health-related risk attitude. While some evidence suggests that risk preferences are not stable across contexts (Barseghyan, Prince, & Teitelbaum, 2011), Dohmen et al. (2011) find a relatively strong correlation of risk attitudes in different contexts including financial matters and health. Another concern about decisions of survey respondents in hypothetical situations, such as choices over hypothetical income gambles (e.g., Fang et al., 2008), is that individuals may actually behave differently in real life situations (Anderson & Mellor, 2008). Some evidence, however, suggest that measures for risk preferences based on hypothetical situations are associated with risk-taking behavior (e.g., smoking) as well as decisions on holding insurance coverage or on investments in risky assets (e.g., Barsky, Juster, Kimball, & Shapiro, 1997). Most studies that examine risk preferences in LTCI and the Medigap insurance market rely on health-related behaviors that capture the *cautiousness* of individuals including risk-reducing activities (e.g., having a flu shot, blood test for cholesterol, mammogram and seat belt use) as well as the refraining of risky activities (e.g., alcohol consumption and smoking). Basically, cautiousness can be considered closely related to risk aversion. However, it may well be the case that more risk averse individuals do not put more effort into preventive activities (Dionne & Eeckhoudt, 1985; Jullien, Salanié, & Salanié, 1999). Thus, while more risk averse individuals can be assumed to buy insurance coverage with a higher probability, it is an empirical question whether that also applies to more cautious individuals (Finkelstein & McGarry, 2006). There is some evidence of a significantly negative relationship between health-related behaviors (i.e., smoking, alcohol consumption, obesity and the non-use of a seat belt) and an experiment-based measure of risk aversion. This indicates that these health-related behaviors are consistently affected by the attitude towards risk (Anderson & Mellor, 2008).

The empirical work on private LTCI and Medigap insurance indicates that the role of risk preferences as a source of advantageous selection varies across insurance markets. In LTCI markets, the empirical evidence predominantly suggests that risk aversion contributes to advantageous selection (Browne & Zhou-Richter, 2014; Cutler et al., 2008; Dardanoni et al., 2016; Dardanoni & Li Donni, 2016; Finkelstein & McGarry, 2006; Gan et al., 2015; Su & Spindler, 2013) even though there are few exemptions. For instance, the studies on the German LTCI market find that individuals with additional VPHI policies are more likely to hold complementary private LTCI.[16] While the findings of Browne and Zhou-Richter (2014) suggest that preference for insurance coverage is an important source of advantageous selection, Bauer et al. (2017), however, conclude that the association between the holding of other types of insurance and claims for LTC benefits is mixed. Concerning the individual’s cautiousness, Cutler et al. (2008), for instance, do not identify a systematic relationship of risky behaviors (e.g., smoking) and nursing home use, but find that risk preferences proxied by preventive health care and seat belt are a source of advantageous selection in the U.S. LTCI market. Similar, Browne and Zhou-Richter (2014) find that the individual’s level of pessimism contributes to advantageous selection, which may be explained by an overestimation of the loss probability and a more cautious behavior. However, they find that individuals who engage in active sports only infrequently are more likely to have a higher risk of needing LTC, but not less likely to hold LTCI. This is in line with Costa-Font and Rovira-Forns (2008) who do not identify self-assessed risk aversion as a significant determinant of LTCI coverage. Nevertheless, Dardanoni and Li Donni (2016) estimate that the welfare loss in the U.S. LTCI market

[16] This is consistent with findings for other VPHI markets (Buchmueller et al., 2013; Lange et al., 2017).

due to a lack of premium differentiation based on the individual's cautiousness is about 7.5% to 10% of total insurance coverage costs.

Studies on the U.S. Medigap insurance market predominantly provide evidence that risk aversion is rather unimportant in explaining advantageous selection even though more risk averse individuals are more likely to have Medigap insurance (Cutler et al., 2008; Dardanoni et al., 2016; Fang et al., 2008; Keane & Stavrunova, 2016; Zimmer, 2012). Fang et al. (2008) and Keane and Stavrunova (2016), for instance, find that risk aversion only slightly affects the relationship between insurance coverage and risk. An explanation for this finding is that the health status of less risk averse individuals is not particularly bad. Similar, Cutler et al. (2008) do not identify a systematic association between risk preferences and expected claims in this insurance market. Consistent with findings of Dardanoni et al. (2016), they show that some proxies for risk preferences, such as preventive health activities, act to reinforce adverse selection, while some proxies for risk aversion, such as seat belt use, contribute to an offsetting of adverse selection. These findings are in line with some evidence for other VPHI markets indicating that risk preferences are not an important driver for advantageous selection (e.g., Buchmueller et al., 2013).[17] Bolin et al. (2010), for instance, do not find that the negative coverage-risk correlation among individuals aged 50 years and older in European VPHI markets is driven by heterogeneous risk preferences and suggest that the negative coverage-risk correlation is more likely to be explained by a successful screening by insurance companies based on observable health conditions.

2.3.3.3 Sociodemographic Characteristics

Relative to the individual's risk attitude, sociodemographic characteristics are usually observable for insurers, but may still be drivers for selection effects if and only if they are not used for risk classification. Particularly, the individual's age at the uptake of insurance is basically used for risk classification in private LTCI markets as well as in the Medigap insurance market and is thus not considered a potential source of selection. As other socioeconomic traits, such as income and education, are generally found to be associated

[17] It should be noted that some evidence suggests that risk preferences is a source of advantageous selection in VPHI markets. Schmitz (2011), for instance, finds that the self-assessed risk aversion of men with respect to health contributes to advantageous selection in the German market for supplementary insurance for hospital visits.

with VPHI demand (Kiil, 2012), and as these factors are not used for risk classification in LTCI markets and in the Medigap insurance market, they are potential drivers for selection. Findings of Zimmer (2012), for instance, suggest that socioeconomic characteristics, including income and education, affect the relationship between Medigap insurance coverage and health care expenditure. While he does not consider the impact of each these traits on the coverage-risk correlation separately, several studies examine the association of specific socioeconomic characteristics with insurance coverage and risk occurrence.

The evidence on income and education as a driver for selection effects is mixed. Some empirical findings suggest that *wealth* or *income* is a source of advantageous selection in the U.S. LTCI market (Finkelstein & McGarry, 2006) and in the Medigap insurance market (Fang et al., 2008; Keane & Stavrunova, 2016). Finkelstein and McGarry (2006), for instance, show that individuals with more wealth are more likely to buy LTCI, but less likely to enter a nursing home. The finding of a positive association of wealth and LTCI coverage is consistent with results of Costa-Font and Rovira-Forns (2008) and can be explained by the existence of a public program like Medicaid in the U.S., which is a substitute for private LTCI especially for individuals with lower wealth (Pauly, 1990). Likewise, some studies on the Medigap insurance market show that *education* contributes of advantageous selection (Dardanoni et al., 2016; Fang et al., 2008; Keane & Stavrunova, 2016). In line with these findings, Bauer et al. (2017) show that a higher socioeconomic status based on the individual's occupation and residential location is positively associated with complementary LTCI coverage in Germany, but negatively with the probability of suffering from LTC costs.

Similar to some evidence for other VPHI markets insurance (e.g., Bolhaar et al., 2012), some findings, however, are not consistent with income and education as important drivers for advantageous selection. For instance, Dardanoni and Li Donni (2012) do not find that wealthier and more educated individuals are more likely to buy Medigap insurance based on a recursive bivariate probit model. Similar, other studies do not identify a significant or clear association of income with insurance coverage (Browne & Zhou-Richter, 2014; Dardanoni et al., 2016; Zimmer, 2012) or of education with insurance coverage (Costa-Font & Rovira-Forns, 2008). Finkelstein and McGarry (2006) even show that less educated individuals are both less likely to hold LTCI and to use LTC, which is rather consistent with adverse selection based on education.

Concerning *race*, there is some evidence that this factor is relevant for selection effects. Keane and Stavrunova (2016), for instance, observe that Hispanics and blacks are less likely to hold Medigap insurance and have a lower health expenditure risk after controlling for health. In addition, they identify these measures as one of the most important determinants of Medigap insurance. The findings concerning the association of blacks and Hispanics with Medigap insurance is supported by Zimmer (2012). Similar, Finkelstein and McGarry (2006) find that non-whites relative to whites as well as Hispanics relative to non-Hispanics are less likely to use nursing homes and to hold LTCI. Even though this observable characteristic contributes to adverse selection, it is unlikely that insurers can use it for risk classification due to ethical reasons.

The *marital status* and the *number of children* of individuals are further observable factors for insurance companies that are not used to determine insurance premiums in LTCI markets and the Medigap insurance market. Concerning the latter, Keane and Stavrunova (2016) find some evidence that married individuals are more likely to hold insurance coverage and that the marital status is a source of adverse selection in this insurance market. It should be noted, however, that the effect of marital status on the coverage-risk correlation is not isolated from the effect of race, which seems to play a more important role for selection effects in this market relative to marital status. Zimmer (2012), who examine the holding of employer-provided supplemental coverage and Medigap insurance coverage separately, find that marriage is significantly and positively correlated with the holding of employer-provided supplemental insurance, but negatively with having a Medigap policy. His findings do not suggest that marital status contributes to selection effects into Medigap insurance.

With respect to LTCI, marital status as well as the number of children are of particular interest as they are proxies for the availability of informal caregivers. The theoretical paper by Pauly (1990) proposes that individuals who prefer to be cared for by their children, may decide not to buy LTCI as this may reduce the incentives for their children to provide informal care for them in favor of formal care (e.g., in a nursing home).[18] For the U.S. LTCI market, Finkelstein and McGarry (2006) find that having more children is negatively correlated with the probability to buy LTCI and to use a nursing home. Similar, Ko

[18] This phenomenon is also called *intrafamily* moral hazard (Pauly, 1990).

(2016) provides evidence of substantial adverse selection arising from private information about the availability of informal care as this factor is negatively associated with nursing home use and LTCI coverage. Based on findings of equilibrium analyses of the LTCI market, she suggests that pricing on child demographics (e.g., the gender and residential proximity of the caregiving child) may substantially reduce this adverse selection and may lead to welfare gains by increasing the LTCI coverage rate of low-risk individuals with better availability of informal care. For the German LTCI market, however, the empirical evidence does not suggest that the availability of informal caregivers is an important driver for selection effects. Browne and Zhou-Richter (2014) show that individuals who are unmarried or not living with one's spouse are higher risk types compared to married individuals who live with their spouse, but are not significantly more likely to hold LTCI. Likewise, having fewer children does not significantly affect the probability to buy LTCI. Similar, Bauer et al. (2017) do not find that people who live in regions with a higher share of single adults are significantly more likely to hold complementary LTCI.

2.3.3.4 Further Attributes

Some studies, particularly on the Medigap insurance market, examine further potential sources of selection, which may be classified as "behavioral" factors (Keane & Stavrunova, 2016). One important factor is the elderly's *cognitive abilities* measured, for instance, by scores on numeracy and word recall. Empirical evidence suggests that cognition has a relatively large positive impact on the probability to buy Medigap insurance and is a key source of advantageous selection in this insurance market as elderly with higher cognitive abilities are healthier (Dardanoni et al., 2016; Fang et al., 2008; Keane & Stavrunova, 2016). This finding is in line with Paccagnella et al. (2013) who analyze determinants of the purchase of VPHI among people aged 50 and older in eleven European countries. They show that heads of the household with better cognitive abilities are more likely to hold VPHI in most countries. Due to the importance of this factor in this market, Fang et al. (2008) discuss several possible pathways for this characteristic as a source of advantageous selection. They provide some preliminary evidence that a potential association of cognitive abilities with search costs to find lower Medigap premiums does not appear to be important. As alternative explanations they suggest that elderly with higher cognitive abilities are more able to evaluate whether the holding of Medigap insurance is worthwhile or that they are more aware of potential future health risks even though they are healthier.

Further behavioral factors that contribute to advantageous selection in the U.S. Medigap insurance market are the *longevity expectation* as measured by the individual's subjective probability to reach the age of 75 years and older as well as the length of the individual's *financial planning horizon* (Fang et al., 2008; Keane & Stavrunova, 2016). While these behavioral factors may play an important role in the decision to purchase LTCI coverage, there is a lack of evidence concerning their effect on the relationship between LTCI coverage and LTC expenditure risk. In a recent study, Gottlieb and Mitchell (2015) suggest a model of narrow framing based on prospect theory. The idea of their model is that individuals, who are subject to narrow framing, tend to make decisions in isolation and consider insurance as a risky investment that is worth if the premiums are lower than the indemnities paid by the insurance company. Using HRS data, they find evidence that individuals with narrow framing are significantly less likely to buy LTCI. In addition, their results indicate that the narrow framing effect on the holding of LTCI coverage is much higher than the effect of the individual's risk aversion, cautiousness or the self-assessed probability of entering a nursing home. It should be noted, however, that they do not examine the empirical relevance of narrow framing as a source of selection.

Browne and Zhou-Richter (2014) examine the individuals' *self-assessed financial preparation for the risk of LTC expenditure*, which may be associated with income, risk preferences and LTCI purchase, as a source of selection in the German private LTCI market. They identify this factor as the main driver for adverse selection in this insurance market because individuals, who feel well financially prepared in case of LTC, are more likely to hold LTCI and to become a nursing case. Their findings suggest that financially well prepared individuals are more aware of their higher risk of LTC expenditures and invest more in protecting themselves against this risk by purchasing LTCI.

Finally, Fang et al. (2008) and Keane and Stavrunova (2016) find that individuals with higher uncertainty in their health expenditures as measured by the variance are less likely to hold Medigap insurance even though that uncertainty is positively associated with the mean of health care expenditure. They thus interpret the variance of health care expenditure as a source of advantageous selection in this insurance market. Possible explanations for this puzzle, as discussed by Fang et al. (2008), are an underestimation of the variance or crowding out effects on Medigap by public-funded health care, such as by Medicaid.

2.4 Conclusion

Health care and LTC expenditure risk are important financial risks for the elderly population. While markets for VPHI and private LTCI may be an option to counteract out-of-pocket risks related to health care and LTC, these markets may suffer from inefficiencies due to asymmetric information or unused observables and related selection effects. This paper reviewed the empirical evidence on the presence and the sources of selection effects in private LTCI markets and in the U.S. Medigap insurance market.

The empirical evidence predominantly suggests that both adverse and advantageous selection are present in these markets due to multidimensional private information, which is consistent with evidence for some other VPHI markets (e.g., Bolhaar et al., 2012; Buchmueller et al., 2013). The evidence concerning the dominating selection effect in private LTCI markets is ambiguous. In the U.S. LTCI market, adverse and advantageous selection rather offset each other in the aggregate as shown by Finkelstein and McGarry (2006). The evidence on selection behavior in other private LTCI markets, such as the German market for private complementary LTCI, points to different directions concerning the dominating selection effect. Future research should especially extend the still sparse evidence on selection effects in LTCI markets in countries other than the U.S. because LTCI markets differ in their institutional settings. Results for the U.S. LTCI market are not necessarily representative for LTCI markets in other countries. In the U.S. Medigap insurance market, most studies provide evidence that advantageous selection rather than adverse selection is the dominating selection effect. While some evidence suggests that it is less likely that advantageous selection in this market is driven by cream skimming of insurance companies, an interesting direction for future research is to examine to what extent a negative coverage-risk correlation is supply-side or demand-side driven. Findings of some recent studies that focus on the insurance coverage for prescription drug expenditures among the elderly U.S. population suggest that both adverse and advantageous selection exist concerning insurance coverage for prescription drugs. As this may be explained by multidimensional private information, more research should be done on sources of selection in this field.

Theory proposes private information on the risk type as the primary source of adverse selection (e.g., Rothschild & Stiglitz, 1976). The evidence on this type of private information particularly in private LTCI markets is ambiguous. Some evidence suggests that private information about risk among those individuals, who are unlikely to be rejected and thus actually can buy LTCI, is not a key source of adverse selection (Braun et al., 2017; Hendren, 2013; Ko, 2016). The findings of Hendren (2013) indicate that individuals with certain observable bad health conditions are rejected as they have significant private information about their risk type. Thus, future research should sufficiently control for possible rejections by insurance companies when analyzing asymmetric information and selection effects. Possible explanations why some individuals particularly with bad self-assessed health are not more likely to buy private LTCI may be unawareness concerning LTC risks or difficulties in predicting one's own future LTC risk. Recent studies show that experience with LTC affect one's own LTCI demand as this may increase the awareness concerning the LTC risk (e.g., Coe, Skira, & Van Houtven, 2015; Courbage & Roudaut, 2008; Tennyson & Yang, 2014). Following Coe et al. (2015), experience with LTC could therefore be explicitly addressed in future research on asymmetric information and selection behavior in LTCI markets. In addition, findings of some studies (e.g., Oster et al., 2010) suggest that genetic testing affects the individuals' private information on their risk type and may aggravate adverse selection.

While theory proposes risk aversion as a key source of advantageous selection (de Meza & Webb, 2001), the empirical evidence suggests that the role of risk preferences with respect to selection effects varies across insurance markets. Studies on LTCI markets predominantly identify this factor as a driver for advantageous selection even though some findings are not consistent with risk aversion as a source of advantageous selection. Possible explanations for different results are differences in the used data as well as in the measures for risk preferences. In the U.S. Medigap insurance market, empirical evidence suggests that the individuals' risk attitude is rather of minor importance with respect to selection effects.

As some sociodemographic characteristics are not used by insurance companies in private LTCI markets and in the Medigap insurance market for risk classification, they are potential sources of selection effects. With some exceptions, there is empirical evidence suggesting that particularly income or wealth is a source of advantageous selection in these markets. While some studies find that race contributes to selection effects, it is unlikely that insurers are allowed to use it for risk classification due to ethical reasons. Nevertheless, an interesting direction for future research is to examine the pathway through which race leads to selection effects. Family characteristics, such as the marital status and the number of children, play an important role in LTCI markets as they can be considered as proxies for the availability of informal caregivers. There is evidence that the availability of informal caregivers contributes to adverse selection in the U.S. LTCI market. This is not corroborated by the sparse evidence on selection behavior in other LTCI markets, specifically in the German market for complementary LTCI. Future research could extend these findings by considering not only the marital status or the number of children, but more specific proxies for the availability of informal care. Examples that have been used in the literature on the demand for LTCI are the beliefs about the availability of informal care (e.g., Coe et al., 2015; Ko, 2016), the number of sons and daughters or whether children live in the same household (e.g., Bonsang & Schoenmaeckers, 2015; Van Houtven, Coe, & Konetzka, 2015).

Furthermore, the evidence on the Medigap insurance market shows that longevity expectations as well as the planning horizon and, in particular, cognitive abilities are sources of advantageous selection. There is, however, still need for future research with respect to the channel through which these factors impact selection effects. In addition, there is lack of evidence concerning these factors as potential drivers for selection effects in private LTCI markets.

Summing up, there is strong evidence of multidimensional private information in the markets for Medigap insurance and private LTCI, which cover important financial risks of the elderly. This may lead to inefficiencies in these markets concerning the insurance coverage of at least some individuals (e.g., Finkelstein & McGarry, 2006). Some recent findings suggest that the use of sources of selection effects for risk classification could decrease inefficiencies in those markets (Dardanoni & Li Donni, 2016; Ko, 2016).

3 Selection Behavior in the Market for Private Complementary Long-term Care Insurance in Germany[19]

Abstract

In this paper, we analyze selection effects in the German market for private complementary long-term care insurance (CompLTCI) contracts within a static and dynamic framework. Using data on more than 98,000 individuals from a German insurance company, we provide evidence that advantageous selection is dominating in this market, with respect to both the decision to buy a CompLTCI policy and the decision about the extent of CompLTCI coverage. We identify occupational status, residential location and the holding of further supplementary health insurance policies as unused observables contributing to selection effects in this market. Our results suggest that non-linearities in the relationship of potential sources of selection with insurance coverage and risk should be considered. A panel data analysis shows that an increase in health insurance payouts is positively correlated with the uptake of CompLTCI, while a decrease in those costs is positively associated with the lapse of CompLTCI. In addition, we find that people in financial distress and of lower socioeconomic status are more likely to let their CompLTCI policies lapse.

[19] This chapter is based on joint work with Jan Michael Bauer from the Copenhagen Business School, Jörg Schiller from the University of Hohenheim and Max-Josef Trautinger. This paper is yet unpublished. The candidate´s individual contribution focused mainly on the literature research, the empirical work and the writing. The author wishes to particularly thank Bernard and François Salanié, Georges Dionne, Carine Franc, Michael Hanselmann as well as all the participants at the 43rd annual EGRIE seminar, the 3rd EuHEA PhD student-supervisor conference, the CEAR/MRIC Behavioral Insurance Workshop 2016 and the Annual Meeting 2017 of the Deutscher Verein für Versicherungswissenschaft e.V. (DVfVW) for their helpful comments. The author also gratefully acknowledges financial support from the DVfVW.

3.1 Introduction

The aging of the population in virtually all industrialized countries has become a great burden for financing LTC (OECD/European Commission, 2013).[20] Public LTC coverage, such as basic mandatory LTCI in Germany, however, does not cover the full costs of care, leading to a risk of high out-of-pocket payments for individuals in need for LTC. The private insurance market offers complementary LTCI (CompLTCI) to close this coverage gap in basic LTCI. However, similar to the limited size of the private LTCI market in the U.S. (Brown & Finkelstein, 2009), the number of CompLTCI policies in Germany was only approximately 3.3 m in 2015 (Association of German private healthcare insurers, 2016b), i.e., only approximately 4% of individuals with basic LTCI in Germany held a CompLTCI policy.

The purpose of this paper is to analyze the German CompLTCI market to identify imperfections and related selection effects, as these may lead to market inefficiencies and contribute to the limited demand for private LTCI.[21] This market is appropriate for analyzing selection effects because premiums for CompLTCI in Germany are risk-adjusted on the date of contract signing based on a small number of characteristics, i.e., age and gender. Ex-ante private information of individuals may lead to adverse (e.g., Rothschild & Stiglitz, 1976) and advantageous selection (de Meza & Webb, 2001). Those selection effects – and the related market inefficiencies – may arise not only from unobservable private information but also from the existence of unused observables, i.e., informative observable characteristics that are correlated with both insurance coverage and risk but not used in pricing (e.g., Finkelstein & Poterba, 2014). Our first research question relates to the existence of those selection effects due to private information in the aggregate. For this purpose, we analyze the correlation between CompLTCI and the risk of LTC needs in a static framework. Here, we differentiate between the decision to buy CompLTCI and, if insured, the decision about the amount of CompLTCI coverage to purchase. By examining potential unused observables in a manner similar to Finkelstein and Poterba (2014), we seek to answer a second research question related to the drivers of selection effects in

[20] Considering the population aging, LTC expenses are expected to at least double and might even triple across OECD countries between 2006/2007 and 2050 (e.g., Colombo et al., 2011).

[21] Brown and Finkelstein (2009) summarize several demand-side and supply-side factors that may limit the market for private LTCI.

this market. Based on previous findings (e.g., Browne & Zhou-Richter, 2014; Fang et al., 2008; Finkelstein & McGarry, 2006), our hypothesis is that asymmetrically used information about preferences for insurance coverage and aspects of the socioeconomic status, such as education and income, contribute to selection effects in this market. In addition to selection effects based on ex-ante private information, an ex-post selection may arise from insufficient front-loading in a situation with long-term contracts and one-sided commitment (e.g., Hendel & Lizzeri, 2003). This may contribute to the limited demand for LTCI policies, such as in the U.S. (e.g., Finkelstein et al., 2005). Hence, by examining the lapse and uptake behavior in a dynamic framework, our third research question is what characterizes the in- and outflow of the insured collective over time. This may provide important insights into the stability of the risk pool of CompLTCI policyholders. Note that the focus of this paper is on selection effects rather than information asymmetry because the latter is not a necessary condition for such an ex-post selection (Hendel & Lizzeri, 2003).

By using a large dataset from a German private health insurance company and analyzing selection behavior in both a static and dynamic context, we extend previous empirical studies that rely on survey data to test for asymmetric information and selection effects in LTCI markets (e.g., Browne & Zhou-Richter, 2014; Finkelstein et al., 2005; Finkelstein & McGarry, 2006). Moreover, we contribute to the literature on unused observables (e.g., Finkelstein & Poterba, 2014) in insurance markets and the sources of selection effects, especially of advantageous selection. Our empirical results provide evidence of asymmetric information in the German CompLTCI market and indicate that advantageous selection is the dominating selection effect. We find that occupational status, residential location, and the holding of further supplementary health insurance policies are unused observables contributing to selection effects in this market. Another contribution our paper makes to the literature is that our results suggest that the effect of characteristics on insurance coverage and risk may be heterogeneous. By analyzing LTCI uptake and lapse behavior, we show that the decision to hold and retain CompLTCI is affected by a change in health insurance payouts. In addition, individuals with lower socioeconomic status and financial problems are more likely to drop CompLTCI coverage.

The remainder of this paper proceeds as follows. Section 3.2 provides an overview of the German LTCI market. Section 3.3 summarizes the theoretical background and related empirical literature on selection effects in insurance markets. Section 3.4 describes the data and the empirical models used for analyzing selection effects in this market. Section 3.5 reports and discusses the results of our analysis, and Section 3.6 concludes the paper.

3.2 Private Complementary Long-term Care Insurance in Germany

In Germany, approximately 88% of the population is covered by SHI, while approximately 12% has substitutive PHI (Federal Ministry of Health, 2017). Since 1995, all citizens have been required to be insured by the statutory LTCI. A basic principle of the German LTCI scheme is that LTCI follows health insurance (Schulz, 2010). Thus, statutory LTCI can be divided into two forms: First, SHI members are usually insured by social LTCI. Second, PHI enrollees are insured by the mandatory private LTCI, which is the focus of our paper. Premiums for the basic private LTCI are risk-adjusted at the date of contract signing based on the individual's age and state of health (Association of German private healthcare insurers, 2016a). By law, the type and scope of benefits of the mandatory private LTCI are equivalent to those in the social LTCI (§ 23 Social Code Book XI). Insured persons are entitled to claim benefits for LTC if independent experts confirm their need for LTC in a review. The need for LTC is legally defined and requires that the insured need help in the long-term, i.e., for at least six months (§ 14 Social Code Book XI). If it is determined that the insured are eligible for LTC, the experts assign them to one of three possible care levels.[22] People in a higher care level receive more benefits. In the basic private LTCI, enrollees can choose between cash benefits for informal home care, reimbursement of part of the LTC costs for formal care or combinations of both. Since 2013, people with a considerably limited ability to cope with daily activities (for instance, due to dementia) but who are not assigned to one of the care levels may also obtain these types of benefits at a lower level than the lowest care level. However, statutory LTCI only partly covers the costs of LTC (Association of German private healthcare insurers, 2016a). Hence, out-of-pocket payments for LTC benefits in Germany are substantial.[23]

[22] Due to reform of the German LTCI scheme, the number of care levels changed from three to five in 2017.

[23] In Germany, the average out-of-pocket payments for people, who are in need for full-time inpatient LTC, are about 1,700 euros per month (Association of German private healthcare insurers, 2017).

More than one third of all LTC costs in 2013 were financed by out-of-pocket payments (Rothgang, Kalwitzki, Müller, Runte, & Unger, 2015).[24]

Enrollees in the mandatory private LTCI are permitted to purchase private CompLTCI coverage directly from private health insurers to reduce the coverage gaps of basic LTCI. Generally, the PHI market, including the market for CompLTCI, can be regarded as oligopolistic (Hofmann & Browne, 2013). In 2015, the total number of CompLTCI policies was approximately 3.3 m, compared to only approximately 0.8 m in 2005 (Association of German private healthcare insurers, 2016c).[25] While the number of CompLTCI policies is increasing, the demand is still rather low. Among CompLTCI policyholders, most individuals have a CompLTCI with daily cash benefits (Association of German private healthcare insurers, 2016b); these policies are the focus of this paper. The cash benefits depend on the recipient's care level, the chosen tariff and the type of LTC, but they do not depend on the actual costs of LTC. In line with basic LTCI, CompLTCI policyholders only receive benefits from CompLTCI if an individual is assigned to a care level. If LTC is indeed needed, the daily cash benefits are freely available to the beneficiaries.

At the date of contract signing, CompLTCI premiums are generally risk-based on the individual's gender as well as the age.[26] The rather limited underwriting and hence a limited premium differentiation may lead to selection effects concerning both the uptake and extent of CompLTCI. Contracts are guaranteed renewable (Pauly et al., 1995). As insurers are committed to the contract terms and enrollees may opt out of their contracts, there is one-sided commitment. Since the policyholders' health status deteriorates over time, CompLTCI policies are front-loaded in order to cover higher expected LTC costs in older age (Hendel & Lizzeri, 2003). The front-loading ensures that premiums are independent of individual changes in health status for the entire contract duration. Hence, policyholders are completely insured against the *individual* reclassification risk. However, the participating nature of CompLTCI contracts, where policyholders participate in the risk

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[24] See Schulz (2010) for more detailed information on the German LTC system.

[25] Since 2013, private health insurers may additionally offer government-funded CompLTCI policies. In 2015, nearly 0.7m (i.e., about 21%) of CompLTCI policies were government-funded (Association of German private healthcare insurers, 2016b). In our paper, however, we will focus on non-funded policies.

[26] Since the introduction of unisex tariffs in December 2012, private health insurers have been prohibited from using gender as a criterion for determining premiums. Moreover, insurers may reject applicants based on their health status or need for LTC at the date of contract signing.

pool's performance, leads to a *collective* reclassification risk. When actual LTC expenditures exceed calculated (expected) costs, insurers have the right to adjust premiums for all policyholders of the risk pool (Hofmann & Browne, 2013; Nell & Rosenbrock, 2008). The lack of consumer commitment and higher incentives for low-risk policyholders to drop CompLTCI coverage may increase the collective reclassification risk due to a worsening of the risk pool over time (Brown & Finkelstein, 2009; Hofmann & Browne, 2013). In extreme cases, this worsening of the risk pool may endanger the protection against the individual reclassification risk (Finkelstein et al., 2005; Nell & Rosenbrock, 2008). Overall, the rather limited ex-ante premium differentiation for CompLTCI as well as the lack of consumer commitment may lead to market inefficiencies due to selection effects.

3.3 Theoretical Background and Related Literature

Our paper is closely related to two strands of literature. First, we rely on and contribute to the literature on adverse and advantageous selection based on ex-ante private information. In classic models of asymmetric information in insurance markets (e.g., Rothschild & Stiglitz, 1976), individuals have only private information about their risk of loss, i.e., private information is one-dimensional. In a separating equilibrium, high-risk individuals choose policies with higher coverage compared to low-risk individuals. According to the model of Rothschild and Stiglitz (1976), in the context of CompLTCI in Germany, people with a high risk of needing LTC are more likely to buy CompLTCI or choose higher coverage compared to low-risk individuals. The basic empirical prediction of adverse selection models in a market equilibrium is the so-called "positive correlation hypothesis", i.e., there is a positive correlation between the individual's risk of loss and the amount of insurance coverage selected conditional on all individual characteristics used by insurers for pricing. This prediction seems to be quite robust if the insurance market is perfectly competitive (Chiappori et al., 2006). Several studies have found a positive coverage-risk correlation in different insurance markets, such as in annuity insurance or health insurance markets (for a review, see Cohen & Siegelman, 2010). In a closely related paper, Browne and Zhou-Richter (2014) find a positive coverage-risk correlation in the German private LTCI market using data from the GSOEP. This is consistent with Oster et al. (2010), who provide evidence for adverse selection in the U.S. LTCI market when individuals have increased private information on their risk (obtained through genetic testing) with respect to carrying HD.

It should be noted that finding a positive correlation is not a sufficient condition for the existence of adverse selection, as such a correlation may also arise from the presence of moral hazard, i.e., reverse causality may be present (e.g., Chiappori et al., 2006; Dionne, 2013). In the latter case, individuals with a high level of insurance coverage have fewer incentives to put effort into prevention, leading to higher risks compared to individuals with lower insurance coverage (*ex-ante* moral hazard); they may also use more benefits due to decreased marginal costs (*ex-post* moral hazard). Cohen and Siegelman (2010) and Dionne (2013) discuss several approaches to disentangle different information problems, such as the causality test of Dionne, Michaud, and Dahchour (2013), which uses dynamic data to separate moral hazard from adverse selection.

While the prediction of a positive coverage-risk correlation is quite robust in a competitive insurance market, the coverage-risk correlation may be of any sign under asymmetric information in an imperfectly competitive market (Chiappori & Salanié, 2013). This may be explained by unobservable heterogeneity in preferences for insurance, in addition to heterogeneity in risk (Cutler et al. 2008). Hemenway (1990) and de Meza and Webb (2001) suggest that a reversal of the positive correlation prediction can be explained by individuals who are more likely to purchase insurance coverage and who simultaneously put more effort into prevention to decrease their risk of loss. Such a mechanism leads to an “advantageous selection" for insurance companies, as insurance coverage is more likely to be chosen by low-risk types. Although, in the theoretical model of de Meza and Webb (2001)[27], risk aversion is a source of advantageous selection, essentially any private information that individuals have about a characteristic with a positive association with insurance coverage but a negative association with risk can be considered a driver of advantageous selection (Fang et al., 2008). Some empirical evidence suggests that multidimensional private information and the resulting selection effects are important in different insurance markets, such as in LTCI markets (Cutler et al., 2008). Finkelstein and McGarry (2006) find that people with private information about their own high risk are more likely to hold LTCI in the U.S. LTCI market. However, this adverse selection is offset by advantageous selection, which explains the absence of a positive correlation between insurance coverage and admission to a nursing home. Their findings suggest that

[27] De Meza and Webb (2001) base their theoretical model on a competitive insurance market. However, administrative costs in processing claims play a crucial role in the existence of the equilibrium.

wealth and risk preferences are sources of advantageous selection in this market. Using survey data, Browne and Zhou-Richter (2014) also find that both selection effects are present in the German private LTCI market even though adverse selection is predominant in that insurance market. They identify the preference for insurance, as measured by the number of additional complementary health insurance policies, as a source of advantageous selection in the German private LTCI market.[28] Fang et al. (2008) provide evidence that cognitive abilities and socioeconomic characteristics (e.g., income and education) are sources of advantageous selection in the U.S. Medigap insurance market.

In another closely related paper, Finkelstein and Poterba (2014) suggest that the identification of observable characteristics that are not used by insurance companies for pricing but correlate with insurance coverage and the risk of loss (i.e., unused observables) indicates that the insurance market suffers from asymmetrically used information. They provide evidence of asymmetric information in the U.K. annuity market by identifying residential location (proxied by the individual's postcode) as an unused observable during the period of their study; they find that the socioeconomic status of an individual's residential location is correlated with insurance demand and with the individual's risk of loss. As shown by Kesternich and Schumacher (2014), unused observables may exist in an equilibrium in an imperfectly competitive insurance market with costly market entry.[29]

The second strand of literature addresses selection effects and dynamic market inefficiencies due to one-sided commitment that may arise for risk-averse individuals who want to insure against the individual reclassification risk (e.g., Pauly et al., 1995) in long-term contracts. In a situation with one-sided commitment (i.e., a lack of commitment from only the insured), low-risk types learning about their risk over time may have an incentive to drop their long-term contracts (Hendel & Lizzeri, 2003). Consistent with their predictions, Hendel and Lizzeri (2003) find that front-loading reduces incentives to cancel insurance policies and that more front-loading helps to retain a better risk pool by decreasing the probability of lapsing in the U.S. life insurance market. In line with these findings, there is some evidence in the German health insurance market that low-risk individuals

[28] Browne and Zhou-Richter (2014) consider this individual characteristic to be related to risk aversion.

[29] Kesternich and Schumacher (2014) also discuss further explanations for the existence of unused observables.

are more likely to drop their basic PHI coverage (Hofmann & Browne, 2013) or supplementary hospital insurance coverage (Lange et al., 2017). Similarly, with respect to LTCI, Finkelstein et al. (2005) and Browne (2006) find that people with a lower LTC risk are less likely to retain LTCI policies over time in the U.S. market. Such an *ex-post* selection may lead to a worsening of the risk pool and therefore higher premiums for LTCI (Brown & Finkelstein, 2009). Dynamic market inefficiencies resulting from an incomplete lock-in of low-risk types (due to insufficient front-loading) may be one factor explaining the limited size of the U.S. LTCI market (Browne, 2006; Finkelstein et al., 2005). It should be noted that this type of selection may be based on the symmetric learning of both insurance companies and consumers, as shown in the model of Hendel and Lizzeri (2003). Konetzka and Luo (2011), however, find little evidence for a worsening of the risk pool due to policy lapse in the U.S. LTCI market and conclude that other drivers, such as a decrease in assets, play a more important role in lapse behavior compared to an improved health status.

In this paper, we contribute to the literature on asymmetric information and selection effects as well as on lapse behavior in LTCI markets. While prior literature is mostly based on survey data, our paper uses insurer data. In addition, we test for selection effects in a static and dynamic framework. While, for instance, Browne and Zhou-Richter (2014) also analyze the German private LTCI market with a similar research focus, they use survey data with information on private LTCI coverage only from 1992, i.e., before the implementation of mandatory basic LTC coverage in Germany. Not only has the German market grown substantially since then, as shown in the previous section, we also examine lapse and uptake behavior over time. In contrast to their findings, we show that advantageous selection is dominating in the German LTCI market. Moreover, we extend the literature by focusing our analysis on unused observables, such as the individual's occupation, in the German CompLTCI market. Another contribution we make to the literature is that we consider heterogeneous effects of characteristics on the risk of loss and insurance coverage when testing for sources of selection.

3.4 Data and Methods

3.4.1 Data and Specification of Variables

In our paper, we use data from a German private health insurance company that sells insurance policies throughout Germany, but is regionally focused on one federal state.[30] Our data include information on health insurance and LTCI policies concluded between 1960 and 2014. We observe claims for each policy between 2006 and 2014. In our analysis, we restrict our sample in three ways. First, we exclude SHI enrollees because we only have information about their LTC risk if they hold a CompLTCI policy from this private health insurance company. Thus, we do not have a control group among SHI enrollees with respect to LTC risk. Second, we exclude civil servants to avoid any complexity arising from differences between civil servants and individuals not employed as civil servants.[31] Third, similar to Browne and Zhou-Richter (2014), we only include individuals aged 40 years and older in 2006, i.e., the first year of observing insurance payouts, as the risk of needing LTC substantially increases with age. Hence, our final sample consists of 98,305 individuals. Table A.1 in the Appendix summarizes, by data source, all variables that we use in our analysis.

As a risk measure in our empirical models, we use several proxies. First, we use a dichotomous variable that indicates 1 if there was any insurance claim for the mandatory LTCI between 2006 and 2014, and 0 otherwise (*LTCprob*). This measure neglects the intensity of the individual impairment but allows for a clear identification of LTCI needs.

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[30] It should be noted that, theoretically, people might buy CompLTCI policies from more than one insurance company. While this could be an obstacle to analyzing asymmetric information with data from one insurance company (Chiappori & Salanié, 2013), we argue that it is very unlikely that individuals will purchase CompLTCI policies from different insurers, as they would suffer from higher transaction costs if they were to buy CompLTCI policies from more than one insurer without benefiting. It would only make sense for the insured to purchase additional insurance from another insurer if they wanted to purchase coverage that exceeds the maximum daily allowance from one insurance company. However, the maximum daily allowance for CompLTCI must not be exceeded by the daily allowance of all CompLTCI policies, including those bought from other insurers. Moreover, we only find about 1% of the CompLTCI policies providing the maximum possible coverage in our sample. Hence, we conclude that outside options seem to be a minor issue.

[31] Civil servants in Germany receive subsidies for their health care and LTC costs from their employer. In addition, civil servants have a strong incentive to enroll in the PHI, which covers their remaining health care costs (Hofmann & Browne, 2013). Moreover, civil servants enrolled in the substitutive PHI have to be insured in the basic mandatory private LTCI (Association of German private healthcare insurers, 2016a). However, coverage in the basic LTCI is lower for civil servants compared to other enrollees.

Using this dichotomous proxy for risk allows us to exclude any ex-post moral hazard effects that may arise from the choice of the type and scope of LTC services. As a second measure of the insured's risk, we use the natural logarithm of the total cost of payouts from the mandatory LTCI (*lnLTCcost*). Note that we can only observe the annual amount of LTC payouts, and hence, we have no information about the insured's care level. As some of the insured may only receive relatively low payouts from the mandatory LTCI, for instance for care aids, even though they do not need LTC in legal terms, we only consider enrollees as in need for LTC if their payouts exceed the minimum amount of cash benefits for LTC. Here, we take into account that the insured are only eligible for LTC benefits if they need care for at least six months. For instance, we classify people as care-dependent if their LTC payouts in 2006 exceeded 1,230 euros, which equals 6 monthly payouts of cash benefits at the lowest care level.[32] In the panel data analysis, we use a dummy variable that indicates 1 if there was any claim for health insurance benefits (*HCprob*), and we use the natural logarithm of total payouts from health insurance (*lnHCcost*) as a proxy for risk. As the latter variables only consider claims that were submitted to the insurer, we have to take into account that health insurance policies differ with respect to deductibles. To make policyholders comparable with respect to their health insurance benefits, we follow Cohen (2005) and consider only claims for health insurance benefits exceeding the highest possible deductible in these policies (i.e., 1,680 euros).

We measure LTCI coverage in a first step with the dichotomous variable *CompLTCI*, which indicates 1 if an individual holds any type of relevant CompLTCI and 0 otherwise. To measure CompLTCI coverage more precisely, we also use the natural logarithm of the sum of the monthly premiums that individuals pay for their CompLTCI policies (*lnCompLTCIp*). When using this variable as a proxy for insurance coverage, we restrict our sample to CompLTCI policyholders, as non-policyholders do not pay any premiums for CompLTCI.

To control for the risk classification made by the insurance company, we include gender and age as covariates in our models.[33] When analyzing only the sample of CompLTCI

[32] To take into account that people may become dependent at the end of a year, we also checked that the received LTC payouts exceed six monthly cash benefits over 2 successive years.

[33] We include gender because most of the CompLTCI policies in our dataset were signed before the introduction of the unisex tariffs in December 2012.

policyholders, we also control for the year of contract conclusion. We interact all pricing characteristics to ensure, for instance, that every individual with the same age and gender is placed into the same risk class. Including these variables adjusts the coverage-risk correlation for all observable factors used by the insurer to set the individual premium.[34] To check the extent to which these characteristics can predict the premiums for CompLTCI, we regress the premium for CompLTCI on these characteristics as well as the type of CompLTCI policy. In this regression, we interact the pricing characteristics. The type of CompLTCI policy considers the generosity with respect to benefits at the different care levels. We find an adjusted R^2 of 0.9545. In our empirical models, however, it is not feasible to consider each type of CompLTCI policy. As much variation in the premiums can be explained without even considering the year in which the contract was signed ($adj.\mathrm{R}^2 = 0.8221$), our proxies for the characteristics used to determine the CompLTCI premiums are good predictors for placing individuals in different risk classes.

When analyzing the sources of selection, we consider several observable characteristics of the insured that are not used by the insurer to set LTCI prices. Here, we analyze the preference for insurance proxied by the holding of additional health insurance policies, in line with Browne and Zhou-Richter (2014). Specifically, we consider daily sickness benefits insurance and hospital daily benefits insurance because PHI enrollees can purchase both types of insurance policies as supplements to their health insurance coverage.[35] In addition to data of the insurance company, we include further information to our dataset in two ways to test for unused observables. First, the insurance data contain information on occupational status of more than 80% of our sample. We use the International Socio-Economic Index of Occupational Status (ISEI) introduced by Ganzeboom, De Graaf, and Treiman (1992) and assign an index value corresponding to socioeconomic status to each individual.[36] The index values used in this paper are based on ISEI-08[37]

[34] Note that there is no discount for buying several policies from the same insurance company or for choosing higher benefits in the CompLTCI policies.

[35] While sickness benefits insurance policies protect PHI enrollees against the loss of income due to the inability to work caused by sickness, PHI enrollees holding hospital daily benefits insurance receive daily cash benefits for each day during a hospital stay.

[36] As some occupations of the insured in our dataset cannot be assigned an ISEI value, the number of individuals with an ISEI-08 value differs from the number of individuals for whom we have information about occupation.

[37] ISEI-08 is based on the 2008 revision of the International Standard Classification of Occupations (ISCO), i.e., ISCO-08.

(Ganzeboom & Treiman, 2010) and consider the income and education of an individual. Second, following Finkelstein and Poterba (2014), we are able to merge information from the German Census of 2011 and the Eurostat database with the residential location of the insured measured by the first three digits of the insured's postcode. The German Census of 2011 includes detailed data on socioeconomic characteristics for more than 400 rural and urban districts.[38] We use these district-level data to assign data on education, employment status, GDP per capita and marital status to each individual.[39] In addition, we include information on the age pattern (*dependency ratio*) in the residential locations where the individuals live.

3.4.2 Econometric Approach in a Static Setting

For the identification of selection effects based on the individual's private information in a static framework, we rely, in our empirical model, on the idea of the bivariate probit model by Chiappori and Salanié (2000); this model has been applied in several previous studies (see Cohen & Siegelman, 2010 for a review). In a first step, we will assess the coverage-risk correlation to obtain the overall difference in LTC risk between people holding a CompLTCI and people without additional LTCI coverage by estimating the following two-equation model:

$$R_i = \alpha_1 + \alpha_2 X_i + \varepsilon_i \quad (1)$$

$$C_i = \beta_1 + \beta_2 X_i + \vartheta_i \quad (2)$$

In this model, we regress both the individual's *i* risk of receiving benefits from the compulsory (basic) LTCI (R_i) and the CompLTCI coverage (C_i) on a vector of the individual's *i* characteristics (X_i) that are observable to the German CompLTCI insurers and used for determining the premium for CompLTCI. After regressing both equations, we use the residuals (ε_i & ϑ_i) and check their independence by analyzing the correlation co-

[38] These districts in Germany correspond to the units of NUTS level 3.
[39] In most cases, the first three digits of the postcode can be attributed to more than one district. Therefore, we use the mean values of the socioeconomic variables for each residential location.

efficient $\rho\ (\varepsilon_i, \vartheta_i)$. Identifying a correlation between the residuals that is significantly different from zero, i.e., $\rho\ (\varepsilon_i, \vartheta_i) \neq 0$, indicates that R_i and C_i are correlated. This finding would point to the existence of asymmetric information in the aggregate. Based on previous findings and the rather limited underwriting in the German CompLTCI market, we hypothesize that the German CompLTCI market suffers from asymmetric information, leading to adverse and/or advantageous selection.

To identify potential sources for selection, we follow the approach of Finkelstein and Poterba (2014). Their test for unused observables is based on the two regressions in equations (1) and (2):

$$R_i = \delta_1 + \delta_2 U_i + \delta_3 X_i + \varphi_i \tag{3}$$

$$C_i = \theta_1 + \theta_2 U_i + \theta_3 X_i + \omega_i \tag{4}$$

The interpretation of the equations generally follows equations (1) and (2). We separately regress R_i and C_i on the same model that includes an intercept (δ_1 & θ_1), the characteristics used for pricing of the CompLTCI policies (X_i), and the error term (φ_i & ω_i). We also include information about the insured that was not used for calculating the premiums but is available to the insurer (U_i). These unused observables can be on the individual level or on a more aggregated level (such as residential location). Looking at δ_2 & θ_2 allows us to identify characteristics that can drive selection into CompLTCI. A variable that correlates positively with risk ($\delta_2 > 0$), but also significantly increases the uptake of CompLTCI ($\theta_2 > 0$) can be interpreted as a driver of adverse selection. Conversely, if a variable correlates positively with the uptake of CompLTCI ($\theta_2 > 0$) but negatively with risk ($\delta_2 < 0$), then we interpret this variable as a driver of advantageous selection. In line with previous studies (e.g., Browne & Zhou-Richter, 2014), another property of a driver of adverse (advantageous) selection is a substantial change in the coverage-risk correlation represented by $\rho\ (\varepsilon_i, \vartheta_i)$ in a negative (positive) direction, i.e., $\rho\ (\varphi_i, \omega_i) < \rho\ (\varepsilon_i, \vartheta_i)$ ($\rho\ (\varphi_i, \omega_i) > \rho\ (\varepsilon_i, \vartheta_i)$).

3.4.3 Econometric Approach in a Dynamic Setting

In addition to cross-sectional information, the data set provides longitudinal annual costs for each contract with information about the cancellation of CompLTCI between 2008 and 2014 and about the uptake of CompLTCI over the whole observation period (i.e., since 1960). We exploit this information to investigate dynamic selection into and out of CompLTCI over our observation period. In a first step, we base our analysis on a pooled regression model similar to equation (4). Here, rather than merely compare individuals with and without CompLTCI, we focus on people changing their CompLTCI status.

For further longitudinal analysis, in a second step, we use variations in the annual health care costs associated with the year an individual takes up or lapses CompLTCI. In this event study, we assign distinct dummy variables to the years before and after the event. This analysis provides a dynamic understanding of the relationship between the individual's health status and the decision-making concerning CompLTCI. Therefore, we model the annual health care costs and claim occurrence in health insurance as:

$$H_{it} = \beta' X_{it} + \sum_{j=-5}^{5} \gamma_j L_{j,it} + u_t + \varepsilon_{it}, \quad j = -5, -4, \dots, 4, 5 \tag{5}$$

where H_{it} represents the health of individual i at time t measured as the natural logarithm of the annual health care cost (*lnHCcost*) or as a dummy variable indicating the occurrence of at least one claim during the specific year (*HCprob*). X_i represents information about the insured that is used for calculating the premiums. By including dummies for year fixed effects with u_t, we control for unobserved but constant heterogeneity among different years. The L_{it} dummies indicate the years before and after the uptake or lapse in year 0. Given the 9 years of observation, leads and lags of more than 5 years are rarely observed. Therefore, we include those observations in the 5-year dummies.

As individuals can only lapse (buy) CompLTCI if they previously had (did not have) such insurance, we restrict our sample in the following way. For the lapse analysis, we only include individuals who had CompLTCI in 2008, as we only observe lapses after 2007. For the uptake analysis, we include people who did not hold CompLTCI before 2006. Thereby, we make our sample comparable in such a way that all individuals in the sample have the opportunity to experience such an event. As reference for the year dummies, we exclude the group of individuals for whom we do not observe a change in CompLTCI status.

3.5 Results

3.5.1 Descriptive Statistics

Table 3.1 provides summary statistics for the whole sample and by CompLTCI status. Within the sample, 19% of individuals own a CompLTCI. A simple comparison of the means of people who do and do not have CompLTCI suggests that the groups do not differ in their probabilities of claiming LTC benefits and in their average LTC costs; this lack of difference may be at least partly due to the relatively small number of LTC beneficiaries ($n = 923$). However, if we only consider health care costs that exceed the highest possible deductible, the probability of submitting a claim and the total cost of health insurance payouts are higher, on average, for CompLTCI policyholders.[40] In addition, CompLTCI policyholders are more likely to hold daily sickness benefits insurance and hospital daily benefits insurance. With respect to demographics, the average CompLTCI enrollee is more likely to be male and older. Data from the additional sources show that individuals with CompLTCI have a slightly higher ISEI-08 score, i.e., a higher socioeconomic status, and they live in areas with higher socioeconomic status as measured by the proportion of individuals with a higher education entrance qualification, the employment rate, and the GDP per capita in an individual's region.

[40] Considering all claims for health insurance, we also find that CompLTCI policyholders have a higher probability of making claims and higher amounts of health insurance payouts (not presented in Table 3.1).

Table 3.1: Summary Statistics

Variable	Total N	Mean	SD	Min	Max	CompLTCI (Mean) No	Yes
				Individual data			
LTCprob	98,305	0.009	0.096	0	1	0.009	0.009
lnLTCcost	98,305	0.089	0.919	0	12.262	0.089	0.086
HCprob	98,305	0.758	0.428	0	1	0.740	0.836
lnHCcost	98,305	6.687	4.028	0	14.641	6.493	7.498
CompLTCI	98,305	0.192	0.394	0	1	0	1
lnCompLTCIp	98,305	0.571	1.213	0	5.495	0	2.967
dsick_ins	98,305	0.490	0.500	0	1	0.464	0.600
dhosp_ins	98,305	0.247	0.432	0	1	0.211	0.400
male	98,305	0.737	0.440	0	1	0.724	0.791
age	98,305	58.430	8.075	48	98	58.056	60.002
ISEI-08	71,471	55.819	21.457	11.560	88.960	55.620	56.786
				Aggregated data[a]			
educ_sec	98,085	32.977	12.353	16.554	71.000	32.679	34.229
employ	98,085	77.122	3.267	61.400	82.704	76.971	77.757
gdp_10000	98,085	3.381	1.493	1.492	8.684	3.345	3.533
dependency ratio	98,085	58.325	4.867	47.000	68.944	58.351	58.217
single	98,085	27.398	5.328	21.000	42.800	27.428	27.271

Notes: [a] The aggregated data for the variables *educ_sec*, *employ*, *dependency ratio* and *single* are measured as the respective percentage share. The GDP per capita is measured in 10,000 euros. A description of the variables and the source of data for each variable can be found in Table A.1 in the Appendix.

3.5.2 Results of the Static Analysis

3.5.2.1 Existence of Asymmetric Information

Table 3.2 reports the estimated correlation coefficient of the residuals $\rho\ (\varepsilon_i, \vartheta_i)$ of equations (1) and (2). Column (1) shows that $\rho\ (\varepsilon_i, \vartheta_i)$ is negative and significant when equations (1) and (2) are estimated with a bivariate probit model. As shown in column (2) and (3), this result is confirmed when we estimate equations (1) and (2) with a probit model and a linear probability model (LPM) separately for the whole sample. These results point to a significantly negative correlation between the probability of buying a CompLTCI policy and the risk of needing LTC care. Thus, low-risk individuals are more likely to purchase a CompLTCI policy. When considering only the sample of CompLTCI policyholders, column (4) shows that the correlation between the extent of CompLTCI coverage (*lnCompLTCIp*) and the extent of payouts from the mandatory LTCI (*lnLTCcost*) is also significantly negative, i.e., low-risk individuals choose higher CompLTCI coverage than high-risk individuals. These results support our hypothesis that individuals have private information that leads to selection effects in the German CompLTCI market, regarding both the decision to buy a CompLTCI policy and the extent of CompLTCI coverage selected. The negative correlation between insurance coverage and risk indicates that advantageous selection is dominating, which may be explained by multidimensional private information. Following Chiappori and Salanié (2013) and, this suggests that, similar to the German PHI market (Hofmann & Browne, 2013), the German CompLTCI market is not perfectly competitive, i.e., the insurer has some market power.

Table 3.2: Correlation between CompLTCI Coverage and Risk

	(1)	(2) Full Sample	(3)	(4) CompLTCI policyholders
	Biprobit	Probit	LPM	OLS
	LTCprob - CompLTCI	*LTCprob – CompLTCI*	*LTCprob – CompLTCI*	*lnLTCcost - lnCompLTCIp*
Correlation coefficient of residuals $\rho\ (\varepsilon_i, \vartheta_i)$	-0.0624***	-0.0063**	-0.0155***	-0.0325***
Observations	98,305	98,305	98,305	18,908

Notes: The residuals are derived from equations (1) and (2). In column (1), the correlation coefficient is based on a bivariate probit model. The coefficient in column (2) represents the correlation between predicted Pearson residuals. *p < 0.1, **p < 0.05, ***p < 0.01.

3.5.2.2 Unused Observables

After analyzing the existence and the dominant type of selection effects in the German CompLTCI market, we focus on the association of observable characteristics of individuals that are currently not used for pricing CompLTCI with LTC risk and with CompLTCI coverage. Table 3.3 illustrates the regression results of adding potential drivers of selection to our model in equations (1) and (2), considering the full sample. We find a significant and positive correlation of socioeconomic status (as measured by the ISEI-08 value) with CompLTCI coverage, but a significant and negative correlation with the risk of loss. Similarly, individuals from regions with a high proportion of people with higher education entrance qualification and with a higher employment rate are more likely to purchase CompLTCI, but less likely to claim LTC benefits. The relationships of these socioeconomic characteristics with our dependent variables remain robust after adding all covariates simultaneously in columns (4) and (5) as well as (9) and (10). Moreover, the correlation between CompLTCI coverage and risk of loss declines from negatively significant ($\rho\ (\varepsilon_i, \vartheta_i) = -0.0504;\ p = 0.090$)[41] to insignificant ($\rho\ (\varphi_i, \omega_i) = 0.0388; p = 0.195$) after including these socioeconomic variables in the model simultaneously (not reported in Table 3.3). These findings suggest that both occupational status and the residential location of an individual are unused observables. Related information about the socioeconomic status on an individual level and on a district level contributes to advantageous selection in the German CompLTCI market. This is consistent with previous studies that have also found socioeconomic characteristics, such as education and wealth, to be sources of advantageous selection (e.g., Fang et al., 2008; Finkelstein & McGarry, 2006).

The results of our proxies for preference for insurance are mixed. Holding daily sickness benefits insurance is negatively correlated with the risk of loss and positively with insurance coverage. Moreover, the coverage-risk correlation is, while still significant, lower after controlling for this characteristic (column (3)). However, the negative correlation of holding this type of insurance with the risk of loss becomes insignificant after

[41] Note that the correlation coefficient of the residuals based on a bivariate probit model without controlling for potential divers of selection is slightly different from that in Table 3.2 We used here the same sample ($n = 71{,}358$) for the models with and without socioeconomic characteristics to make the correlation between the residuals comparable.

controlling for all covariates simultaneously (column (4)).[42] As this type of insurance compensates individuals for the loss of earnings, it is relevant only for employed people. Therefore, we also analyzed the relationship of holding daily sickness benefits insurance with our dependent variables only for people aged 65 and younger, and we still found a positive correlation with CompLTCI coverage and a negative correlation with the risk of loss. This finding is consistent with Browne and Zhou-Richter (2014), who find the preference for insurance to be a source of advantageous selection.

In contrast, holding hospital daily benefits insurance can be regarded as a driver of adverse selection because it is positively correlated with both CompLTCI coverage and the probability of claiming LTC benefits when risk is measured by the probability of needing LTC. This is consistent with Lange et al. (2017), who find that people in Germany with supplementary hospital insurance coverage are more likely to suffer from sickness in the future. One possible explanation for these mixed results with respect to supplementary health insurance is that some people have private information about their risk of suffering from diseases that are likely to require treatment in a hospital. This would lead to a higher probability of purchasing hospital daily benefits insurance and CompLTCI. On the other hand, people buying daily sickness benefits insurance may be relatively highly risk averse, leading to a higher demand for this type of supplementary health insurance and CompLTCI, but a lower LTC risk due to cautious health behavior. Another explanation could be that some people have private information about their risk of becoming sick and suffering from income loss due to a resulting inability to work, but this situation is not linked to a higher risk of needing LTC. Nevertheless, we suggest that the holding of supplementary health insurance is another unused observable.

Table 3.4 depicts the results for sources of selection for the subsample of CompLTCI policyholders. Here, we find that the ISEI-08 value and the holding supplementary health insurance coverage are positively correlated with the extent of CompLTCI coverage. Additionally, the employment rate of an individual's district is positively correlated with the amount of CompLTCI coverage. Individuals who live in areas with a high share of single

[42] This is at least partly due to the reduced sample. Adding all potential sources of selection except the ISEI-08 value to the model, the correlation between holding daily sickness benefits insurance and the risk of loss is still significantly negative.

adults purchase less CompLTCI coverage. While some variables, such as educational attainment and the share of single adults in an individual's region, are significantly negatively correlated with the risk of needing LTC, these relationships are weak and even insignificant in the full model, as shown in column (4). The holding of hospital daily benefits insurance is positively correlated with the probability of receiving LTC payouts. Hence, among CompLTCI policyholders, only the holding of this type of supplementary health insurance can be identified as a source of adverse selection when all covariates are considered simultaneously.[43]

The results in Tables 3.3 and 3.4 suggest that most potential sources of selection consistently affect the decision to buy a CompLTCI policy and the amount of CompLTCI coverage. However, only one variable (*dhosp_ins*) can be identified as a consistent source of either adverse or advantageous selection for the full sample, on the one hand, and the restricted sample of CompLTCI policyholders, on the other hand. This finding indicates that unused observables may contribute to selection effects concerning the decision to purchase a CompLTCI, but not concerning the decision to choose the amount of CompLTCI coverage among the CompLTCI policyholders.

[43] The relationships of all observable characteristics with our risk proxy remain robust when risk is measured with the natural logarithm of LTC payouts (*lnLTCcost*).

Table 3.3: Sources of Selection (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Adding potential sources separately			Adding all potential sources simultaneously		Adding potential sources separately			Adding all potential sources simultaneously	
	LTCprob	CompLTCI	$\rho\ (\varphi_i, \omega_i)$	LTCprob	CompLTCI	lnLTCcost	lnCompLTCIp	$\rho\ (\varphi_i, \omega_i)$	lnLTCcost	lnCompLTCIp
Socioeconomic characteristics										
ISEI-08	-0.0028***	0.0014***	-0.0459	-0.0023**	0.0012***	-0.0004***	0.0010***	-0.0110***	-0.0003***	0.0008***
	(0.001)	(0.000)	(p = 0.112)	(0.001)	(0.000)	(0.000)	(0.000)	(p = 0.003)	(0.000)	(0.000)
educ_sec	-0.0029***	0.0044***	-0.0606***	-0.0083**	0.0039**	-0.0011*	0.0028***	-0.0247***	-0.0009*	0.0022
	(0.001)	(0.001)	(p = 0.003)	(0.004)	(0.002)	(0.001)	(0.001)	(p = 0.001)	(0.000)	(0.001)
employ	-0.0131***	0.0394***	-0.0580***	-0.0146***	0.0284***	-0.0028***	0.0292***	-0.0225***	-0.0022***	0.0215***
	(0.004)	(0.004)	(p = 0.005)	(0.005)	(0.003)	(0.001)	(0.002)	(p = 0.000)	(0.001)	(0.002)
gdp_10000	-0.0141*	0.0376***	-0.0617***	0.0237	0.0312**	-0.0023	0.0255***	-0.0231***	0.0045	0.0162
	(0.009)	(0.007)	(p = 0.003)	(0.024)	(0.014)	(0.002)	(0.006)	(p = 0.000)	(0.003)	(0.010)
dependency ratio	0.0028	-0.0025	-0.0627***	0.0075	-0.0082**	0.0002	-0.0013	-0.0232***	0.0007	-0.0061**
	(0.003)	(0.002)	(p = 0.002)	(0.007)	(0.004)	(0.001)	(0.002)	(p = 0.000)	(0.001)	(0.003)
single	-0.0042*	-0.0036	-0.0631***	0.0046	-0.0217***	-0.0007	-0.0038**	-0.0233***	0.0001	-0.0130***
	(0.002)	(0.003)	(p = 0.002)	(0.007)	(0.004)	(0.001)	(0.002)	(p = 0.000)	(0.001)	(0.003)
Preference for insurance										
dsick_ins	-0.1338***	0.4485***	-0.0564***	-0.0648	0.3919***	-0.0303***	0.3261***	-0.0213***	-0.0146***	0.2582***
	(0.035)	(0.010)	(p = 0.005)	(0.040)	(0.013)	(0.005)	(0.008)	(p = 0.000)	(0.004)	(0.010)
dhosp_ins	0.0648***	0.5215***	-0.0714***	0.1042**	0.4380***	0.0042	0.4287***	-0.0237***	0.0104	0.3477***
	(0.031)	(0.010)	(p = 0.000)	(0.045)	(0.014)	(0.007)	(0.010)	(p = 0.000)	(0.006)	(0.014)
Pricing characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant				-4.0768***	-3.9652***				-0.1172	-1.6840***
				(0.731)	(0.388)				(0.108)	(0.278)
Observations				71,358					71,358	
Correlation between residuals $\rho\ (\varphi_i, \omega_i)$				-0.0480 (p = 0.114)					-0.0102*** (p = 0.006)	

Notes: The number of observations slightly differs due to missing values. The coefficients in columns (1)-(5) are based on a bivariate probit model. Robust standard errors for each coefficient and p-value for the correlation coefficient of the residuals in parentheses, respectively. When aggregated characteristics are included into the model, standard errors are clustered at a district level. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 3.4: Sources of Selection (CompLTCI Policyholders)

	(1)	(2)	(3)	(4)	(5)
	Adding potential sources separately			Adding all potential sources simultaneously	
	LTCprob	lnCompLTCIp	$\rho\ (\varphi_i, \omega_i)$	LTCprob	lnCompLTCIp
Socioeconomic characteristics					
ISEI-08	-0.0000	0.0006**	-0.0214**	0.0000	0.0007**
	(0.000)	(0.000)	(p = 0.018)	(0.000)	(0.000)
educ_sec	-0.0001*	-0.0000	-0.0308***	-0.0001	0.0013
	(0.000)	(0.000)	(p = 0.000)	(0.000)	(0.001)
employ	-0.0001	0.0026*	-0.0308***	-0.0000	0.0030*
	(0.000)	(0.001)	(p = 0.000)	(0.000)	(0.002)
gdp_10000	-0.0009*	0.0025	-0.0307***	-0.0001	0.0081
	(0.000)	(0.003)	(p = 0.000)	(0.001)	(0.009)
dependency ratio	0.0001	0.0005	-0.0308***	-0.0000	-0.0042*
	(0.000)	(0.001)	(p = 0.000)	(0.000)	(0.002)
single	-0.0002*	-0.0022***	-0.0311***	-0.0001	-0.0096***
	(0.000)	(0.001)	(p = 0.000)	(0.000)	(0.002)
Preference for insurance					
dsick_ins	-0.0030**	0.0267***	-0.0308***	-0.0019	0.0257**
	(0.001)	(0.010)	(p = 0.000)	(0.001)	(0.012)
dhosp_ins	0.0024*	0.0360***	-0.0315***	0.0025*	0.0295***
	(0.001)	(0.009)	(p = 0.000)	(0.001)	(0.011)
Pricing characteristics	Yes	Yes	Yes	Yes	Yes
Constant				0.0250	28.2273***
				(0.026)	(0.570)
Observations				12,170	
Correlation between residuals $\rho\ (\varphi_i, \omega_i)$				-0.0212** (p = 0.020)	

Notes: The number of observations slightly differs due to missing values. Robust standard errors for each coefficient and p-value for the correlation coefficient of the residuals in parentheses, respectively. When aggregated characteristics are included into the model, standard errors are clustered at a district level. *p < 0.10, **p < 0.05, ***p < 0.01.

In a next step, we divide all non-binary variables into quintiles to examine potential non-linear effects of individuals' characteristics on our outcome variables. This enables us to obtain a clearer picture of whether the association of the covariates with our outcome variables is heterogeneous. As shown in Table 3.5, the correlation of the characteristics that we identify as sources of advantageous selection (i.e., the ISEI-08 value as well as the educational attainment and the employment rate of an individual's region) with CompLTCI is consistently lower in the first quintile (reference group) compared to higher quintiles (column (2)). However, these correlations do not increase linearly. For instance, consistent with similar findings of McCall, Mangle, Bauer, and Knickman (1998) regarding the association of income and LTCI, the pattern of the correlation of the ISEI-08 value with CompLTCI is U-shaped, with its strongest association in the third quintile. Thus, the demand for CompLTCI increases up to the third quintile of the ISEI-08 distribution and, while still significantly higher than the first quintile, decreases afterwards. The identification of these characteristics as sources of selection is mainly driven by the highest quintiles, as the negative correlation with the risk of loss is only significant in those quintiles. Moreover, while we could not identify the GDP per capita in an individual's district as a source of selection in our previous analysis (see Table 3.3), we find that individuals living in regions with a GDP per capita in the highest quintile are lower risks and significantly more likely to hold CompLTCI than individuals in the lowest quintile. This indicates that individuals living in relatively wealthy regions contribute to advantageous selection.

Table 3.5: Heterogeneous Effects of Potential Sources of Selection on CompLTCI and Risk

Independent Variable	(1) LTCprob	(2) CompLTCI
ISEI-08		
Second Quintile	-0.0031	0.2411***
	(0.057)	(0.018)
Third Quintile	-0.0761	0.3126***
	(0.061)	(0.018)
Fourth Quintile	-0.0649	0.2584***
	(0.060)	(0.018)
Fifth Quintile	-0.1562***	0.0686***
	(0.059)	(0.018)
educ_sec		
Second Quintile	0.0335	0.2039***
	(0.043)	(0.034)
Third Quintile	-0.0952**	0.2275***
	(0.046)	(0.035)
Fourth Quintile	-0.0444	0.1124***
	(0.043)	(0.038)
Fifth Quintile	-0.1119**	0.2676***
	(0.044)	(0.030)
employ		
Second Quintile	-0.0155	0.1345***
	(0.041)	(0.042)
Third Quintile	-0.0130	0.2096***
	(0.043)	(0.038)
Fourth Quintile	-0.1086***	0.3345***
	(0.041)	(0.033)
Fifth Quintile	-0.1238***	0.3475***
	(0.041)	(0.033)

Continued on next page

Independent Variable	(1) LTCprob	(2) CompLTCI
gdp_10000		
Second Quintile	-0.0484	0.1682***
	(0.043)	(0.043)
Third Quintile	-0.0046	0.0932**
	(0.043)	(0.045)
Fourth Quintile	0.0084	0.2201***
	(0.040)	(0.043)
Fifth Quintile	-0.0899**	0.1995***
	(0.041)	(0.042)
dependency ratio		
Second Quintile	0.0429	0.0186
	(0.045)	(0.048)
Third Quintile	0.0551	0.0614
	(0.041)	(0.040)
Fourth Quintile	0.0858*	0.0146
	(0.045)	(0.038)
Fifth Quintile	0.0170	-0.0154
	(0.042)	(0.039)
single		
Second Quintile	-0.0063	0.1144***
	(0.041)	(0.034)
Third Quintile	-0.0638	0.0701*
	(0.042)	(0.039)
Fourth Quintile	-0.0959**	-0.0509
	(0.046)	(0.047)
Fifth Quintile	-0.0877**	-0.0161
	(0.042)	(0.040)

Notes: The number of observations slightly differs due to missing values. Robust standard errors for each coefficient in parentheses. When aggregated characteristics are included into the model, standard errors are clustered at a district level. Omitted reference categories: First quintiles of the independent variables. *p < 0.10, **p < 0.05, ***p < 0.01.

It should be noted that one potential issue could be that the unused observables and the related characteristics are not necessarily exogenous.[44] We argue, however, that endogeneity is unlikely to be an issue with respect to using residential location and occupational status as unused observables. The characteristics based on residential location are measured on an aggregated regional level. We argue that they are less likely to suffer from the issue of reverse causality or an omitted variable bias based on unobserved individual characteristics. Similarly, the insurance company collects information about the individual's occupation only once, i.e., at the time of the individual's first health insurance enrollment. This information is not frequently updated. Hence, occupational changes as a consequence of LTC-related health shocks seem to be less likely.

[44] Dionne, La Haye, and Bergerès (2015), for instance, use several instruments to take account of possible endogeneity in testing for the presence of asymmetric information.

3.5.3 Results of the Dynamic Analysis

Our finding of the negative coverage-risk correlation, which indicates advantageous selection as the dominating selection effect, is based on a static perspective on the sample. In this section, we turn to a dynamic analysis of how the sample of CompLTCI policyholders changes over time. Here, we consider the lapse as well as the uptake of CompLTCI policies. Table 3.6 reports the results of a pooled regression of these outcome variables on health insurance payouts and on several other characteristics. Considering columns (1) and (2), we find that CompLTCI policyholders with higher health insurance payouts are less likely to let their CompLTCI policies lapse. Consistent with previous findings (e.g., Finkelstein et al., 2005), this points to an ex-post risk-based selection due to a lack of consumer commitment even though CompLTCI policies are front-loaded. Moreover, individuals with higher socioeconomic status, as measured by the ISEI-value, are also less likely to let their policies lapse. Consistent with Konetzka and Luo (2011), this suggests that people with lower socioeconomic status are more likely to suffer from financial problems, which increases the probability that they will let their policies lapse. This is supported by the strong positive correlation of having an "emergency treatments only" tariff (designed for non-paying customers in financial distress) with a lapse in CompLTCI.[45] As shown in columns (3) and (4) of Table 3.6, our findings similarly suggest an adverse selection with respect to the uptake of CompLTCI, as individuals with higher health insurance payouts are more likely to purchase CompLTCI. Consistent with the findings of our static analysis, our results show that individuals with a higher socioeconomic status (as measured with the ISEI-08 value and the employment rate of an individual's district) and individuals who hold a supplementary health insurance policy are more likely to buy CompLTCI.

[45] PHI enrollees who are not able to pay their regular health insurance premiums over several months are assigned to an "emergency treatments only" tariff, which only covers the costs of acute sickness and pain, as well as pregnancy and maternity. In 2014, about 0.1 m PHI enrollees held this tariff (Association of German private healthcare insurers, 2016b).

Table 3.6: Pooled Regression for Lapse and Uptake of CompLTCI

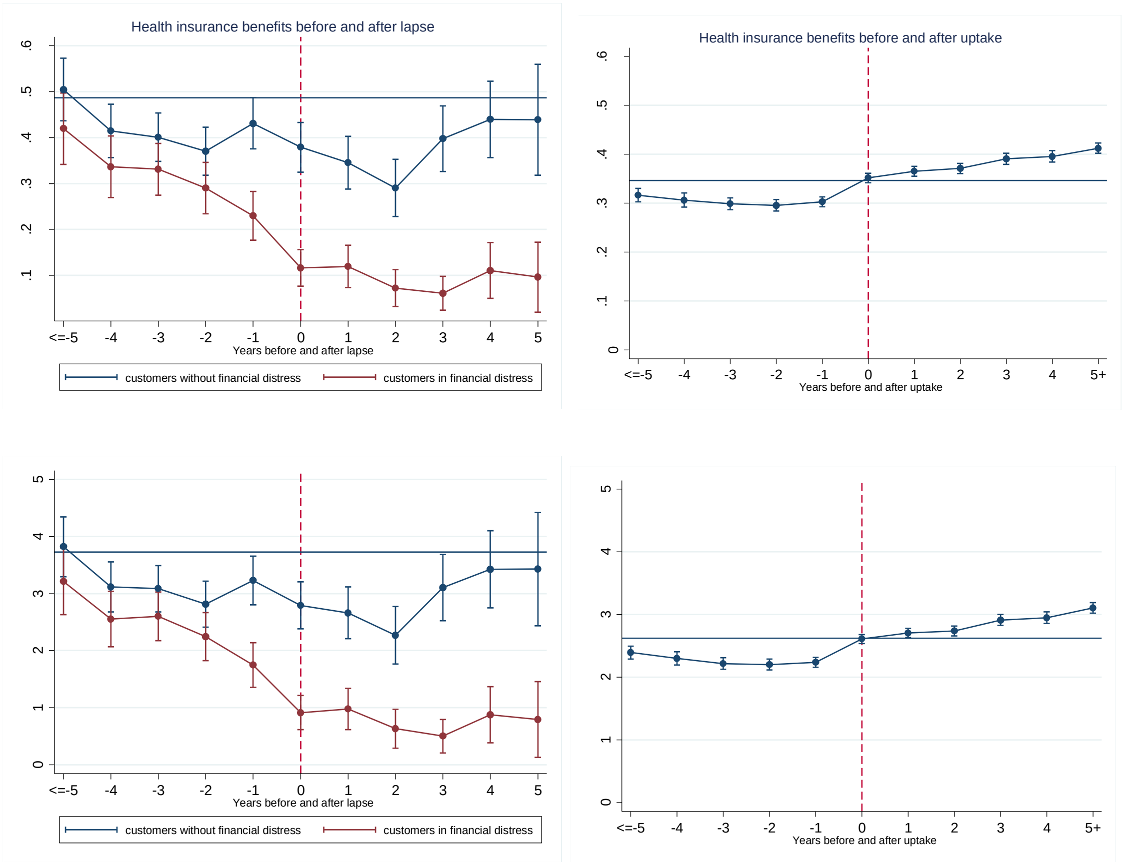
Dependent variable	LTCI_lapse		CompLTCI	
	(1)	(2)	(3)	(4)
Independent variable	Adding covariates separately	Adding covariates simultaneously	Adding covariates separately	Adding covariates simultaneously
lnHCcost	-0.0060***	-0.0022***	0.0021***	0.0010***
	(0.001)	(0.001)	(0.000)	(0.000)
ISEI-08	-0.0006***	-0.0003***	0.0003***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
educ	-0.0002	0.0002	-0.0001	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)
employ	-0.0014**	-0.0001	0.0056***	0.0060***
	(0.001)	(0.001)	(0.000)	(0.001)
gdp_10000	-0.0018*	-0.0009	-0.0002	-0.0002
	(0.001)	(0.002)	(0.001)	(0.002)
dependency ratio	0.0007**	0.0008	0.0003	-0.0013**
	(0.000)	(0.001)	(0.000)	(0.001)
single	-0.0001	0.0006	-0.0012***	-0.0009
	(0.000)	(0.001)	(0.000)	(0.001)
dsick_ins	-0.0103**	-0.0075	0.0492***	0.0437***
	(0.004)	(0.005)	(0.002)	(0.003)
dhosp_ins	-0.0013	-0.0019	0.0507***	0.0409***
	(0.003)	(0.004)	(0.003)	(0.004)
tariff_non-payer	0.8709***	0.8521***		
	(0.022)	(0.024)		
Pricing characteristics	Yes	Yes	Yes	Yes
Constant		-0.0597		-0.3621***
		(0.217)		(0.067)
Observations		8,321		66,408

Notes: The number of observations slightly differs due to missing values. Robust standard errors for each coefficient in parentheses. When aggregated characteristics are included into the model, standard errors are clustered at a district level. *p < 0.10, **p < 0.05, ***p < 0.01.

Figure 3.1 illustrates the health insurance benefits held by individuals in the periods before and after two events: lapse and uptake of CompLTCI. The marginal effects on health insurance benefits before and after these events are reported in Table A.2 in the Appendix. Considering first the lapse behavior of CompLTCI policyholders (graphs on the left), we find that the probability and amount of health insurance payouts for people in financial distress (red line) decline until the CompLTCI policy lapses. After the lapse, health insurance payouts remain at a low level. One obvious reason for this finding is that people with financial problems are more likely to drop CompLTCI coverage, and this tariff provides only basic coverage, such as for the costs of acute treatment and severe pain. Considering individuals without financial distress (blue line), the probability of claiming health insurance benefits as well as the amount of health insurance payouts are at a higher level, but still consistently below the average of CompLTCI enrollees who did not let their policies lapse. Similar to the trend for people in financial distress, the probability of claiming insurance benefits as well as the amount of health insurance benefits decrease around the year of the lapse. If health insurance payouts mainly reflect the individual's health status, which is positively correlated with LTC costs in the future, this result may point to ex-post selection, which would be consistent with previous studies (e.g., Finkelstein et al., 2005; Hofmann & Browne, 2013); i.e., people with better health and lower LTC risks are more likely to let their CompLTCI lapse. However, as shown in Figure 3.1, the health insurance payouts of policyholders without financial problems rise again some years after the lapse in insurance, and costs actually return to their pre-lapse level. While we cannot exclude the possibility that the decreased health insurance payouts around the year of lapse reflect an improvement in health, we suggest that it is more likely that individuals' financial problems explain these findings. Individuals with a deductible as part of their health insurance policy may omit medical treatments to reduce health care expenses, which will lower health insurance payouts for a short period of time. Moreover, as shown in Table 3.6 and Figure 3.1 (red lines), people of lower socioeconomic status and/or with financial problems are more likely to drop CompLTCI.

The uptake behavior, shown in the graphs on the right, indicates that both the probability and the amount of health insurance payouts of CompLTCI enrollees are lower than the average of non-enrollees before the uptake, but starting in the year of the uptake, both increase to a level above the average of non-policyholders. This may indicate that people with increasing health care costs become more aware of LTC risk or anticipate an increased risk of needing LTC. If health care and LTC costs are positively correlated, this finding would be consistent with adverse selection and hence with a deterioration of the risk pool of CompLTCI policyholders over time.

Figure 3.1: Average Marginal Effects of Lapse and Uptake of CompLTCI Policies on the Probability of Claiming Health Insurance Benefits and the Amount of Health Insurance Payouts.



Note: The horizontal line on each graph represents the outcome variable of the reference group, i.e., people who did not lapse in the graphs on the left and people without a CompLTCI in the graphs on the right. The vertical bars on each point refer to the 95% confidence interval.

3.5.4 The Issue of Moral Hazard

The finding of our static analysis – i.e., that advantageous selection is the dominating selection effect – holds true regardless of the existence of moral hazard, as the latter would imply a positive coverage-risk correlation. Nevertheless, it is of interest to determine the extent to which any selection effect is biased by moral hazard effects. In a first step, we theoretically argue that moral hazard should be of minor importance in the context of the German market for CompLTCI. In addition, we provide empirical evidence that moral hazard is unlikely to bias our results.

From a theoretical perspective, our first argument is that ex-ante moral hazard plays a small role in the LTCI context (similar to the context of health insurance markets) because any behavior leading to ex-ante moral hazard negatively affects the individual's own health (Cutler & Zeckhauser, 2000). Second, ex-post moral hazard effects in the German LTCI market are less likely to be a problem due to the condition that LTC benefits depend on individuals being assigned to a care level by independent experts. Ex-post moral hazard in the German CompLTCI market could result from LTC beneficiaries choosing between different LTC services, such as between receiving LTC at home from a mobile nursing service or receiving more expensive care at a nursing home. Several surveys show that individuals in Germany prefer to receive LTC at home instead of going to a nursing home (Deutsche Gesellschaft für Qualität, 2015; MLP, 2014; R+V Versicherung, 2013). Moreover, as shown by Grabowski and Gruber (2007), the demand for nursing home care is relatively price inelastic. In addition, when we measure risk by the probability of needing LTC, ex-post moral hazard should not be an issue.

To empirically test for moral hazard, we estimate an instrumental variable (IV) model for a regional subsample. The identification of potential moral hazard requires that we exclude the possibility of selection into insurance, which can be estimated using exogenous variation in the uptake of insurance. The instrument in question must predict CompLTCI uptake and be uncorrelated with LTC risk. As an instrument, we rely on the regional density of local banks in the area, as such banks serve as insurance agencies. Close proximity to an insurance agency reduces the costs of uptake and increases the probability of interacting with an insurance agent. The agency density in a region is, however, only exogenous to LTC risk if agents are not able to anticipate future risk development and select themselves into low-risk environments. We argue that this is not the case for two reasons: First, we only rely on local banks that are unlikely to locate themselves in certain areas based on local LTC risks. Second, little is known about the determinants of LTC risk beyond individual age and gender, both of which we use as controls in the IV regression. We therefore account for any possible confounding relationship between the agency density and age and gender distribution.

Table 3.7 shows the estimation results. The LPM displayed in column (1) shows a negative correlation between CompLTCI and the probability of LTC needs. This result again indicates the presence of advantageous selection in the LTCI market, which overshadows potential moral hazard when CompLTCI is endogenous in the regression. For the regional subsample, we observe a similar relationship for the LPM, which suggests that the subsample does not systematically differ from the full sample. The first-stage regression shows that our instrument is sufficiently predictive of insurance uptake, with an F-statistic above the commonly accepted threshold of 10 (Greene, 2012; Stock, Wright, & Yogo, 2002). However, neither the reduced form regression nor the 2SLS estimation show a significant effect on LTC risk. This supports our previous argument that the CompLTCI market is unlikely to suffer from moral hazard and our selection estimates are unlikely to be upwardly biased by the presence of moral hazard.

Table 3.7: IV-approach with Distribution Density as an Instrument for Testing for Moral Hazard

	(1) Full Sample	(2)	(3) Regional Sample	(4)	(5)
			Reduced Form	First Stage	
	LPM	LPM	LPM	LPM	2SLS
Dependent variable	LTCprob	LTCprob	LTCprob	CompLTCI	LTCprob
Independent variable					
CompLTCI	-0.0038***	-0.0048***			0.0134
	(0.001)	(0.001)			(0.041)
distribution_dens			0.0001	0.0128***	
			(0.001)	(0.003)	
First Stage F-statistic					16.294
Observations	98,305	38,537	38,537	38,537	38,537

Notes: Robust standard errors in parentheses. In the regression of the reduced form, the first stage as well as the 2SLS (columns (3)-(5)), standard errors are clustered at the district level because the agency density is measured on a regional level. *p < 0.1, **p < 0.05, ***p < 0.01.

3.6 Conclusions

In this paper, we analyze selection effects in the German market for CompLTCI using data from an insurance company. In a static framework, we provide evidence that individuals with a CompLTCI are lower-risk types than non-enrollees and that CompLTCI policyholders with more insurance coverage are lower risks compared to policyholders with less coverage. These results indicate that people in this market have private information, which leads to advantageous selection as the dominating selection effect – concerning both the decision to buy a policy and the extent of insurance coverage chosen.

This is in contrast to the results of Browne and Zhou-Richter (2014), who find adverse selection to be dominating in the German market for LTCI. Given the design of the German LTCI system, these findings are unlikely to be biased by moral hazard, and we provide additional empirical evidence of this conclusion. An equilibrium involving advantageous selection, which arises from multidimensional private information and offsets adverse selection effects, may also suffer from market inefficiencies (e.g., Fang et al., 2008; Finkelstein & McGarry, 2006).

Testing for sources of selection, we identify the occupation, the residential location and the preference for insurance coverage as unused observables. While both occupation and residential location include information about socioeconomic status that contributes to advantageous selection, our results with respect to holding supplementary health insurance as a source of either adverse or advantageous selection are mixed. We argue that these tests are unlikely to suffer from endogeneity when we test aggregated information based on the residential location and information based on the occupation. The inconsistency – with respect to the sources of selection for the full and the restricted sample of CompLTCI policyholders – suggest that unused observables, which contribute to selection effects concerning the decision to buy CompLTCI, do not necessarily contribute to selection effects concerning the chosen amount of CompLTCI coverage. Moreover, our results indicate that non-linear effects of certain characteristics on insurance coverage and risk should be considered when analyzing sources of selection.

Based on our results of the static analysis, we conclude that the German CompLTCI market is not perfectly competitive. First, following Chiappori and Salanié (2013), in a perfectly competitive market with asymmetric information, only a positive coverage-risk correlation would be predicted. Second, the significant relationships for several potential unused observables suggest that German CompLTCI insurers do not use all observable characteristics of individuals when classifying individuals into risk classes, even though these characteristics are correlated both with insurance demand and with the risk of loss in this market. Following Kesternich and Schumacher (2014), one explanation for the existence of the identified unused observables might be that the existing insurance companies offering CompLTCI in Germany cannot profitably use the unused observables to discriminate between different risk types. Nevertheless, we argue that the selection effects identified here might be gainfully used by insurance companies in the German LTCI market should they want to pursue a more targeted distribution of products.

It should be noted that our finding of advantageous selection in the static framework can be regarded as a snapshot of the risk pool at a given point in time. By examining the change in the risk pool over time in a dynamic framework, we find that individuals with increased health insurance payouts are more likely to buy a CompLTCI and that people with decreased health care costs are more likely to let their CompLTCI policy lapse. People who learn about their low LTC risk over time based on their current health care status and decide to drop CompLTCI coverage might explain this result if health insurance payouts are positively correlated with future LTC risk. In this case, our results suggest that the market suffers not only from adverse selection over time but also from ex-post selection arising from a lack of consumer commitment. The latter would be in line with findings for the U.S. LTCI market (Finkelstein et al., 2005) and the German PHI market (Hofmann & Browne, 2013) and would lead to dynamic market inefficiencies. However, our results also show that health insurance payouts rise again a short time after lapse. One possible explanation for this finding from a behavioral perspective could be that the declined insurance payouts reflect a short-term improvement in health and that this provides individuals with a salient reference point for their expectations about their future health and LTC risks. Accordingly, people may make their decisions to retain CompLTCI based on these factors. While we cannot exclude this explanation, we suggest, in line with Konetzka and Luo (2011), that it is more likely that lapses are driven by financial problems. People with financial problems and a deductible in their health insurance contracts may simply decide to forego or delay medical treatment over a short period to reduce their out-of-pocket expenses on health care. This could also explain the declined health insurance payouts. In addition, these people may decide to drop CompLTCI to eliminate premium payments. This alternative explanation is supported by our finding that lapses are positively associated with financial distress and low socioeconomic status. Moreover, considering our results that people of higher socioeconomic status are less likely to need LTC, the selection of people based on their socioeconomic status may counteract any possible worsening of the risk pool.

Overall, our findings provide solid evidence of the existence of market imperfections and selection effects in the German CompLTCI market. This may lead to inefficiencies with respect to insurance coverage for LTC risks. Note that we do not claim that our data are representative of all PHI companies or the entire population in Germany. Future research could extend our insights into selection behavior in LTC markets by differentiating between different types of LTC. Furthermore, information about health care and LTC costs, as well the lapse of LTCI policies over a longer period of time, might provide more insights into the issue of ex-post selection. In addition, future studies could extend our analysis by focusing on CompLTCI tariffs that are subsidized by the state (“Pflege-Bahr”) and that were introduced in 2013. As insurance companies in this market cannot charge risk-based premiums at the time of contract signing or reject applicants who have no need for LTC, the market for these policies is prone to adverse selection (Ehing, 2015; Jacobs & Rothgang, 2013).

4 Heterogeneous Selection in the Market for Private Supplemental Dental Insurance: Evidence from Germany[46]

Abstract

This paper analyzes the German market for supplemental dental insurance to identify selection behavior based on individuals' private information. The rather limited underwriting by German private health insurers makes this market especially prone to selection effects. Although the standard positive correlation test does not indicate asymmetric information in this market, we conjecture that this outcome may result from sample heterogeneity when adverse and advantageous selection occur simultaneously and offset each other. Examining a large set of potential sources of selection effects, we mainly find that the holding of other SuppHI policies, which is related to risk preferences, contributes to an advantageous selection in this insurance market. Our results suggest that even in the absence of a positive correlation between risk and insurance coverage, the German market for supplemental dental insurance suffers from information asymmetry, which is caused by multidimensional private information.

[46] This chapter is based on joint work with Jan Michael Bauer from the Copenhagen Business School and Jörg Schiller from the University of Hohenheim. The candidate´s individual contribution focused mainly on the literature research, the empirical work and the writing. The underlying manuscript was submitted to *Empirical Economics* for publication. The author wishes to particularly thank Stefan Felder and Peter Zweifel, the University of Ulm as well as all the participants at the 41st annual EGRIE seminar, the 2015 annual meeting of the DVfVW and the 3rd World Risk and Insurance Economics Congress for their helpful comments. The author also thanks the Bertelsmann Stiftung for providing data from the Healthcare Monitor in cooperation with the statutory health insurance fund Barmer GEK. Furthermore, the author gratefully acknowledges financial support from the DVfVW.

4.1 Introduction

Growing health care expenditure has led to a financial burden for health care systems with universal insurance coverage. Increasing copayments and benefits restrictions in public health insurance, while offering a market for VPHI for coverage gaps may be an option to limit public health care expenditure. In many OECD countries, especially dental care for adults is one type of benefits not at all or only partly covered by basic health insurance (Paris et al., 2010) and thus on average, 55% of the total expenditure for dental care was paid for out-of-pocket in 2011 (OECD, 2013). In the German SHI, for instance, insurance coverage for dental benefits has been incrementally reduced. This led to a tripling of SHI enrollees holding a private SuppDI in addition to their SHI coverage between 2004 and 2012. Among several different SuppHI policies, the highest demand is on SuppDI in Germany (Grabka, 2014). However, shifting coverage to VPHI carries a risk of inefficiency since asymmetric information and related selection effects may lead to a suboptimal insurance coverage at least by some individuals (Finkelstein & McGarry, 2006; Rothschild & Stiglitz, 1976).

The purpose of this paper is to analyze selection effects in the German market for SuppDI. This is a particularly appropriate context given that the rather limited underwriting by German private health insurers at the date of contract signing makes this market prone to selection. In a first step, we examine whether SHI enrollees have private information leading to selection effects in the aggregate. Using standard approaches for testing for asymmetric information, such as based on Chiappori and Salanié (2000), we do not find support for the basic prediction that SuppDI coverage correlates positively with the risk of needing dental care. As this finding may result from an offsetting of adverse and advantageous selection, combined with a possible inefficient market outcome (Finkelstein & McGarry, 2006), we analyze whether we identify potential sources of selection in a second step. Based on theory (de Meza & Webb, 2001; Rothschild & Stiglitz, 1976) and previous studies (Buchmueller et al., 2013; Fang et al., 2008; Finkelstein & McGarry, 2006), we focus on risk preferences, socioeconomic characteristics and the individual's health status as potential sources. We mainly find the preference for insurance proxied by the number of other SuppHI policies except SuppDI as the main driver for advantageous selection. This is consistent with Lange et al. (2017) who also find a positive impact of preference for insurance, proxied among others by the holding of other SuppHIs, on

SuppDI coverage. In contrast to their study, which is based on data from the GSOEP, our data include information on dental risk enabling us to analyze selection effects. By providing evidence of heterogeneous selection despite not rejecting the null hypothesis of an insignificant coverage-risk correlation, we complement the mixed evidence on selection effects in markets for private dental insurance (e.g., Godfried, Oosterbeek, & van Tulder, 2001; Srivastava, Chen, & Harris, 2017). More generally and in line with Finkelstein and McGarry (2006), this finding suggests that a coverage-risk correlation is not a necessary condition for information asymmetry in insurance markets. Moreover, using a rich set of data, we extend the empirical literature on sources of selection. We particularly contribute to the still mixed evidence on the role of risk preferences with respect to selection behavior by identifying the holding of other insurance policies as a key source of advantageous selection in this market (e.g., Browne & Zhou-Richter, 2014; Fang et al., 2008). Moreover, our findings are useful for policy implications concerning the decision to decrease coverage in the public health insurance system and to provide the option of VPHI for coverage gaps in the public system.

The remainder of the paper proceeds as follows. Section 4.2 gives an overview of the German health insurance system. Section 4.3 then summarizes the basic theoretical effects of information asymmetry in insurance markets and reviews the related literature. Section 4.4 presents the data and empirical model. Section 4.5 reports and discusses the results of both the main analysis and several robustness checks. Section 4.6 concludes the paper.

4.2 Institutional Background

In Germany, the SHI covers nearly 90% of the population while about 10% has substitutive PHI. SHI has a highly uniform standard benefit package for all funds, one that is quite comprehensive compared to those in other industrialized countries (Beske et al., 2005). Due to rising health care expenditure, out-of-pocket expenses from copayments and standard benefit exclusions have recently been increasing in the SHI (Grabka, 2014). In particular, a 2004 reform changed the 35–50% coinsurance rate for dental prostheses to diagnosis-based fixed benefits covering 50%[47] of the cost of standard treatment (Klingenberger & Micheelis, 2005).[48] Dental prostheses costs exceeding these benefits must be paid out of pocket, subjecting SHI enrollees to an increased financial risk associated with dental care.

To reduce coverage gaps in the SHI benefit package, SHI enrollees may buy SuppHI directly from private health insurers. The German market for PHI including SuppHI is imperfectly competitive (Hofmann & Browne, 2013). SuppHI contracts are guaranteed renewable (Pauly et al., 1995). Among various types of SuppHI available to SHI enrollees, such as SuppDI or supplemental hospital insurance, SuppDI is the most prevalent and has the highest growth rate probably due to the 2004 reform. The proportion of SHI enrollees having SuppDI tripled after the 2004 reform from 5.6% in 2004 to 16.6% in 2012 (Grabka, 2014). The main purpose of SuppDI policies is to reduce out-of-pocket expenses for dental services, especially for dental prostheses. Since only the cost of standard treatment for dental prostheses is partly covered by SHI, SHI enrollees may profit even more from SuppDI policies if they prefer higher quality prostheses. Premiums for SuppDI are generally risk adjusted based on individual age at the date of contract signing and gender.[49] Additionally, insurers may ask applicants about past dental prostheses and advised dental or orthodontic treatment.[50] Yet, the ex-ante premium differentiation for SuppDI is limited, since only few characteristics are used for pricing SuppDI policies. This may lead to selection effects from information asymmetry.[51]

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47 By law, the fixed benefits can rise by 20% (30%) if there is evidence that the insured performs regular prevention and can prove yearly dental check-ups during the last 5 (10) years before treatment.

48 This rule applies to all but low-income SHI enrollees, who are eligible to receive the full cost of standard treatment. According to Barmer GEK, in 2012, about 9% of SHI enrollees received diagnosis-based fixed benefits covering 100% of the cost of standard treatment (Rädel, Hartmann, Bohm, & Walter, 2014).

49 Since the introduction of unisex tariffs in December 2012, gender has been prohibited for determining the premiums for private health insurance policies, such as SuppDI.

50 Moreover, insurers may reject applicants based on risk-related responses. For instance, some insurers reject applicants with missing teeth above a certain threshold. We will take this issue in our empirical model (Section 4.4.2) and in our robustness checks (Section 4.5.2) into account.

51 In addition, there is no consideration of past premium payment history, meaning that the information asymmetry from a lack of ex-ante premium differentiation preserves over time.

4.3 Theoretical Background and Related Literature

The classical type of selection based on asymmetric information is adverse selection. In the standard model with adverse selection (Rothschild & Stiglitz, 1976), individuals have only private information with respect to their risk type. In a separating equilibrium, high-risk individuals choose policies with higher coverage compared to low-risk individuals. In our context, this model predicts that high-risk SHI enrollees purchase SuppDI with a higher probability or – in an extreme case – are the only risk types purchasing SuppDI, meaning that the demand of low-risk individuals is inefficiently low. The basic empirical prediction of adverse selection is that the amount of insurance coverage is positively correlated with the risk of loss controlling for all relevant characteristics used by insurers for risk-based rate making (Chiappori et al., 2006). Numerous studies have confirmed this correlation prediction in different insurance markets (see Cohen & Siegelman, 2010 for a review). In a closely related paper, Godfried et al. (2001) identify adverse selection in the Dutch SuppDI market after dental service exclusion from compulsory health insurance. They show that individuals with poorer dental health or more frequent past dentist visits are more likely to purchase SuppDI than individuals with better dental health or fewer past visits.

However, the prediction of a positive coverage-risk correlation is not only consistent with adverse selection, but may also arise from moral hazard (Chiappori et al., 2006). Based on theory on moral hazard (Pauly, 1968; Shavell, 1979), individuals with SuppDI coverage may reduce their effort into preventive dental care (*ex-ante* moral hazard) or increase their consumption of dental care after occurrence of a dental disease (*ex-post* moral hazard). As discussed by Cohen and Siegelman (2010) as well as Dionne (2013), different approaches have been applied in empirical studies to separate selection effects from moral hazard in insurance markets. One way is based on a randomized or natural experiment, such as the RAND Health Insurance Experiment (Manning, Newhouse, Duan, Keeler, & Leibowitz, 1987). In settings with non-experimental data, one possible approach is to use simultaneous equations models (e.g., Holly, Gardiol, Domenighetti, & Bisig, 1998; Keane & Stavrunova, 2016; Paccagnella et al., 2013; Srivastava et al., 2017).

A crucial limitation of the positive correlation test is that the correlation between insurance coverage and risk occurrence may also be negative in an imperfectly competitive insurance market like the German market for SuppDI (Chiappori & Salanié, 2013). An absence of a positive correlation can be explained either by negligible information asymmetries or, for instance, by unobserved preference heterogeneity in addition to heterogeneity in risk, i.e., multidimensional private information (e.g., Cutler et al., 2008).[52] Hemenway (1990) suggests that a negative risk-coverage correlation can be explained by highly risk-averse individuals that are more likely to buy insurance coverage and invest more in prevention so as to reduce their risk of loss. This mechanism can produce an advantageous selection in a market equilibrium as shown in the theoretical model by de Meza and Webb (2001). Based on this theory, one would expect low-risk individuals to buy SuppDI coverage more likely.

Several recent studies do find evidence for the importance of multidimensional private information in different insurance markets. Srivastava et al. (2017), for instance, find a positive correlation between private dental insurance in Australia and oral health as well as preventive behavior towards dental health (e.g., flossing), which is consistent with advantageous selection. In another related paper, Finkelstein and McGarry (2006) find evidence of multidimensional private information in the U.S. LTCI market. As they do not identify a significant correlation between risk occurrence and LTCI coverage, they conclude that adverse and advantageous selection offset each other in the aggregate. Their findings indicate that a positive coverage-risk correlation is not a necessary condition for implying that an insurance market suffers from inefficiencies due to information asymmetry.

Based on de Meza and Webb (2001), risk aversion is of primary interest as a source of advantageous selection. Some studies provide evidence that factors related to risk preferences contribute to advantageous selection (e.g., Buchmueller et al., 2013; Doiron et al., 2008; Finkelstein & McGarry, 2006; Schmitz, 2011). Browne and Zhou-Richter (2014), for instance, find that preference for insurance, measured by the holding of SuppHI policies, is a source for advantageous selection in the German LTCI market. However, insurance markets differ in whether risk preferences are an important source of advantageous selection. Fang et al. (2008) for instance, find that risk preferences cannot be considered as a source of advantageous selection in the U.S. Medigap insurance market. They suggest that potential sources of advantageous selection, in general, may be any

52 Further possible explanations for the lack of a positive correlation between insurance coverage and risk occurrence are discussed by Cohen and Siegelman (2010).

private information about characteristics that positively correlates with insurance coverage, but negatively with the risk of loss. For instance, there is some evidence that socioeconomic characteristics, particularly wealth or income, contribute to advantageous selection (Buchmueller et al., 2013; Fang et al., 2008; Finkelstein & McGarry, 2006).

The previous literature has provided evidence that indicates that the dominating type of selection and the role of risk preferences with respect to selection behavior is still mixed. Hence, further evidence is required to provide a better understanding of selection effects and their sources that can be used to improve market efficiency. Our paper is, to the best of our knowledge, the first study analyzing heterogeneous selection in the German market of SuppDI based on a rich data set with particularly detailed dental information. We use a comprehensive set of statistical tests to provide robust and novel insights into selection behavior in markets for SuppHI.

4.4 Data and Methods

4.4.1 Data

In our paper, we use data at the individual level from the Healthcare Monitor, a representative survey of a cross-section of the German population.[53] For the present analysis, we rely exclusively on wave 19 (from 2011) because it contains very detailed information of individuals about dental health and dentist visits in addition to information on the general health status, health insurance coverage, socioeconomic characteristics and the number of physician visits. Concerning dental health, respondents were asked whether or not they have periodontitis, dental fillings, implants, dental prosthesis, caries, jaw point pain, missing teeth, toothache, and whether they wear braces or a splint against teeth grinding. With respect to health insurance, the survey collected data whether the respondents are SHI or PHI enrollees and which SuppHI policies they hold. The survey does not provide information about the premiums and the comprehensiveness of the insurance policies. For this wave, a total of 2,200 individuals aged 18 to 79 were contacted by mail, of whom

[53] The Healthcare Monitor (“Gesundheitsmonitor”) is administered since 2001 by the Bertelsmann Stiftung. Since 2011, the SHI fund Barmer GEK has been cooperating with the Bertelsmann Stiftung on the Healthcare Monitor.

over 80% responded (GfK Health Care, 2011). Our final sample consists of 1,781 individuals.

Table 4.1 shows some descriptive statistics divided by insurance status. PHI enrollees (column 1) tend to be older, have higher incomes, and be more predominantly male than SHI enrollees (column 2). With regard to dental health, however, we observe no major differences between the two groups. Given our focus on selection in the SuppDI market, we are particularly interested in differences between individuals with and without a SuppDI policy. Since the insurance coverage covered by SuppDI is already included in most PHI plans, we exclude PHI enrollees ($n = 285$) and only consider SHI enrollees ($n = 1{,}496$) in our analysis. Among individuals with SHI, less than one third (29%) holds a SuppDI policy. The comparison between SHI with (3) and without (4) SuppDI shows that SuppDI policyholders are more likely to be married and, in line with most findings in the literature (see Kiil, 2012 for a review), have a higher income. Srivastava et al. (2017), for instance, show that private dental insurance coverage is positively correlated with income in Australia. Consistent with previous findings (Browne & Zhou-Richter, 2014; Buchmueller et al., 2013; Lange et al., 2017), SuppDI policyholders are more likely to hold further SuppHIs.

To test for selection effects, we must find an appropriate measure for the financial risk associated with dental treatments. Because our data include no information on the specific type of dental care or resulting expenditure for dental treatments, we cannot fully measure individual risk. Rather, we proxy risk by the number of dentist visits. The individuals were asked about the number of dentist visits in the previous twelve months. Table 4.1 shows that SuppDI policyholders go to the dentist more often than the comparison group. This finding might indicate that SuppDI policyholders are higher risks as they are also more likely to have a dental implant or dental filling and less likely to have no dental problems. Simply comparing the numbers for SuppDI enrollees and non-enrollees, however, is inadequate for risk assessment because the former may also be more likely to have annual check-ups. In fact, Table 4.1 confirms that SuppDI policyholders tend to have more preventive dentist visits than non-enrollees.

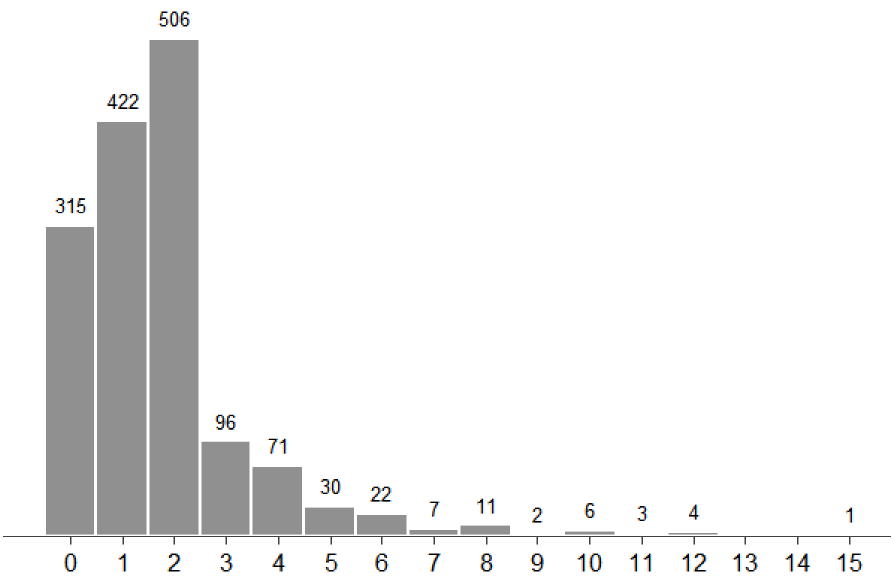
Table 4.1: Descriptive Statistics by Insurance

	PHI	SHI	SHI	
	(1)	(2)	(3) SuppDI	(4)
	All	All	Yes	No
Utilization of dental services				
Dentist visits per year	1.817	1.761	2.049	1.641***
Usual preventive dentist visits per year				
Seldom/only in pain	0.108	0.054	0.022	0.068***
Once in 2 years	0.082	0.032	0.020	0.036
Once	0.354	0.375	0.353	0.384
Twice	0.384	0.490	0.551	0.464***
Three times or more	0.071	0.049	0.054	0.048
Dental issues				
Periodontitis	0.146	0.178	0.159	0.185
Filling	0.623	0.674	0.728	0.651***
Prosthesis	0.384	0.419	0.441	0.409
Implant	0.198	0.105	0.127	0.096*
Braces	0.022	0.021	0.017	0.022
Grind teeth	0.056	0.065	0.076	0.060
Missing teeth	0.078	0.095	0.098	0.093
Toothache	0.011	0.015	0.025	0.011*
Chewing/jaw	0.007	0.022	0.025	0.021
Caries	0.071	0.074	0.061	0.079
No issues	0.123	0.115	0.088	0.126**
Socioeconomic characteristics				
Male	0.687	0.454	0.429	0.464
Age	54.567	49.495	50.324	49.153
Marital status				
Married	0.690	0.576	0.637	0.550***
Widowed	0.030	0.047	0.056	0.044
Divorced	0.067	0.089	0.091	0.088
Single	0.213	0.288	0.216	0.318***
Income	3.690	2.782	2.993	2.695***
A-level	0.657	0.462	0.446	0.468
Employment				
Full time work	0.422	0.389	0.407	0.381
Part time work	0.052	0.123	0.115	0.127
Hourly based work	0.022	0.059	0.061	0.059
Unemployed	0.455	0.358	0.373	0.352
Job training	0.049	0.071	0.044	0.082**
Household size	2.291	2.315	2.341	2.304
Health status				
Self-rated health	3.201	3.135	3.130	3.137
Proxies for risk preferences and health-related behavior				
Number of other SuppHIs	1.160	0.506	1.179	0.228***
Never a smoker	0.545	0.561	0.532	0.572
BMI	26.500	26.428	26.543	26.381
Activity	4.134	3.940	4.034	3.901
Diet				
Fruits	3.179	3.218	3.267	3.198
Vegetables	3.157	3.075	3.137	3.050**
Fast food	1.825	1.822	1.824	1.822
Sweets	2.347	2.411	2.419	2.408
Observations	285	1,496	429	1,067

Notes: Sample size can vary slightly within each variable. Income is measured in €1,000 intervals from < €1,000 up to > €5,000 monthly net household income. Self-rated health: bad = 1 to excellent = 5. Activity: never = 1 to daily = 6. Diet: never/seldom = 1 to daily = 4. The level of significance for the statistical differences in a two-sided *t*-test between the two groups (see columns 3 and 4) is designated as follows: *p < 0.10; **p < 0.05; ***p < 0.01.

To improve our risk measurement, we adjust our risk proxy to disentangle acute treatment visits from preventive check-ups. Figure 4.1 shows the distribution of dentist visits for the whole sample of individuals with SHI. As is evident, many individuals go to the dentist only once or twice a year, which indicates actual treatment or a dental check-up.[54] Since SHI only covers two annual check-ups, we assume that three or more annual dentist visits clearly point to acute treatment. We thus transform our variable for risk (*DentVisits*) into a dummy equal to 1 if an individual went to the dentist more than twice in the previous year, and 0 otherwise. This transformation of the count variable, also used by Godfried et al. (2001), should minimize incorrect measurement of preventive dentist visits as a proxy for risk. In our robustness checks, we consider alternative specifications of the main dependent variable as well as an alternative risk proxy (Section 4.5.2).

Figure 4.1: Number of Dentist Visits for All Individuals with SHI



[54] SHI members have a financial incentive to go for regular dental check-ups because if they do so during the 5 or 10 years preceding treatment, they receive higher benefits for dental prostheses.

4.4.2 Econometric Approach

In a first step, we analyze the coverage-risk correlation to test for asymmetric information in the aggregate. Here, we apply two approaches which have been used in several previous studies (Cohen & Siegelman, 2010). In our first approach ("one-equation approach"), we estimate the relation between the ex-post risk of an individual with respect to dental treatment and SuppDI coverage by specifying the following LPM:

$$P(DentVisits = 1|SuppDI, X, C) = \alpha_0 + \alpha_1 SuppDI + \alpha_2 X + \alpha_3 C \qquad (1)$$

$DentVisits$ is our risk proxy as described in the previous section. $SuppDI$ equals 1 if an individual has SuppDI, 0 otherwise. As the premiums for SuppDIs are generally risk adjusted, we include the vector X to control for the risk classification in SuppDI policies. In line with the pricing of all German health insurers offering SuppDI, we include the insured's age[55] and gender[56]. As insurers may ask applicants about missing teeth, past dental prostheses and advised dental or orthodontic treatment, we also include whether the individual has a dental prosthesis, a dental implant or missing teeth to be more conservative and to reflect the more thorough risk classification used only by some insurance companies. All these variables are included in nonparametric form and fully interacted. Finally, we control in our models for the usual number of annual dentist visits for patients without any major dental issues. We assume these to represent preventive dentist visits (vector C).[57] Hence, this should capture overly cautious individuals, i.e., those getting more than the recommended two annual check-ups. In addition, we control for the individuals' fear of the dentist, which might capture possible skipping of annual check-ups

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[55] As the data are only cross-sectional, we cannot include characteristics related to time of contract finalization. As a proxy, we use current information from the survey. In fact, age at contract entry is decisive for risk classification; however, since the survey does not report this datum, we control for the age of the insured at time of survey. We assume this bias to be relatively small since the majority of policies were finalized after the 2004 health care reform.

[56] As our survey data are from 2011, the introduction of unisex tariffs in December 2012 does not affect our analysis.

[57] Possible answers to the correspondent survey item are "three or more times a year," "about twice a year," "about once a year," "about once in 2 years," or "seldom, only in pain."

or an avoidance of necessary treatments.[58] Because the dependent variable is dichotomous, we also estimate a probit model.

In our second approach ("two-equation approach"), we rely on the bivariate probit model introduced by Chiappori and Salanié (2000) with the following two equations:

$$DentVisits \ = \mathbf{1}(\beta_1 X + \beta_2 C + \varepsilon > 0) \tag{2}$$

$$SuppDI \qquad = \mathbf{1}(\gamma_1 X + \eta > 0) \tag{3}$$

The specifications of the variables are the same as in equation (1). In this approach, we regress both our risk proxy $DentVisits$ and our proxy for insurance coverage $SuppDI$ conditional on X. We only control for vector C in equation (2) since we assume that the frequency of dentist visits without any major dental issues and the fear of the dentist are exogenous in this equation, but do not directly affect the holding of SuppDI. Testing the independency of the residuals by the correlation coefficient $\rho\ (\varepsilon, \eta)$ enables to determine the relationship between $DentVisits$ and $SuppDI$. Finding a correlation between the residuals that is significantly different from zero, i.e., $\rho\ (\varepsilon, \eta) \neq\ 0$, indicates that $DentVisits$ and $SuppDI$ are correlated. This finding would point to the existence of asymmetric information.

The sign of the coefficient of interest α_1 in equation (1) as well as the correlation coefficient $\rho\ (\varepsilon, \eta)$ based on equation (2) and (3) indicate the dominant selection type in the aggregate. Identifying that α_1 or $\rho\ (\varepsilon, \eta)$ is not significantly different from zero may be explained by different effects. First, it could indicate that asymmetric information in the SuppDI market is empirically negligible. Second, it could lead to a false rejection of asymmetric information when both adverse and advantageous selection offset each other in the insurance market. The latter is unlikely to result in an equilibrium that is first best (Finkelstein & McGarry, 2006). Third, an insignificant coverage-risk correlation could also be due to the existence of advantageous selection and an offsetting moral hazard effect positively affecting the coverage-risk correlation. Some studies (e.g., Manning, Bailit, Benjamin, & Newhouse, 1986; Meyerhoefer, Zuvekas, & Manski, 2014) find that

[58] Measured by a 6-item scale from "no fear" to "panic."

having dental insurance positively affects utilization of dental services.[59] However, there is also empirical evidence (see Grembowski, Conrad, Weaver, & Milgrom, 1988 for a review) that documents a rather low price elasticity for dental services. Furthermore, Meyerhoefer et al. (2014), for instance, find that the use of dental services is significantly increased for people holding a dental insurance, but insensitive to variation of out-of-pocket costs. Consistent with previous studies (Manning et al., 1986; Mueller & Monheit, 1988), this finding indicates that varying the mere *level* of dental insurance coverage does not considerably impact the use of dental services. Thus, while we cannot reject a possible bias caused by moral hazard, we conjecture that a moral hazard effect of SuppDI coverage in Germany is rather low since each SHI enrollee is fully covered for basic tooth preservation and at least for 50% of the cost of standard treatment for dental prostheses. We suggest that an insignificant coverage-risk correlation arises at least to some extent from an offsetting effect of heterogeneous selection.

To get a clearer picture on the selection behavior in the SuppDI market, we test for the potential sources of selection effects in a second step. Consistent with previous studies (e.g., Browne & Zhou-Richter, 2014; Finkelstein & McGarry, 2006), we add potential drivers to our basic model in equation (4) and (5):

$$DentVisits = \mathbf{1}(\theta_1 X + \theta_2 C + \theta_3 D + \varphi > 0) \tag{4}$$

$$SuppDI \quad = \mathbf{1}(\vartheta_1 X + \vartheta_3 D + \phi > 0) \tag{5}$$

The interpretation of the equations generally follows equation (2) and (3). Vector D represents potential drivers for selection. Looking at θ_3 and ϑ_3 enables us to examine which characteristics are drivers for selection. Identifying an attribute that correlates positively with the uptake of SuppDI ($\vartheta_3 > 0$) and with the risk of loss ($\theta_3 > 0$) and that substantially changes the coverage-risk correlation represented by $\rho\ (\varphi, \phi)$ in a negative direction (i.e., $\rho\ (\varphi, \phi) < \rho\ (\varepsilon, \eta)$) can be considered as a source of adverse selection. Conversely, finding a characteristic with opposite signs for the correlation with SuppDI

[59] Srivastava et al. (2017), for instance, find that private dental insurance coverage increases the probability of general dental visits which may be interpreted as evidence of ex-post moral hazard. However, as they do not disentangle visits for acute treatment and for dental check-ups, their findings may be also explained by a higher degree of risk aversion of individuals with a private dental insurance.

and risk (e.g., $\vartheta_3 > 0$ & $\theta_3 < 0$) and which leads to $\rho\ (\varphi, \phi) > \rho\ (\varepsilon, \eta)$ can be interpreted as a source of advantageous selection. It should be noted that this holds irrespective of a possible bias caused by moral hazard.

In our analysis, we consider several potential sources of advantageous selection. We focus on characteristics related to risk preferences since risk aversion may be considered as a primary cause of advantageous selection based on de Meza and Webb (2001). Since we cannot measure risk aversion directly, we test a large set of factors that have been related to individual risk preferences in previous studies (Browne & Zhou-Richter, 2014; Buchmueller et al., 2013; Cutler et al., 2008; Finkelstein & McGarry, 2006). First, we examine risky or risk-reducing behavior with variables on the individual's care about his own health (*"Care about health"*), on smoking ("*Never a smoker*"), on the frequency of physical activities ("*Physical activities*"), such as sports or gardening, and on the frequency of eating rather healthy food ("*Fruits*" and "*Vegetables*") and unhealthy food ("*Fast Food*" and "*Sweets*"). Based on the assumption that these measures are likely to be related to risk aversion, we predict that people with a preventive health behavior are more likely to hold SuppDI and less likely to visit dentists for acute treatment. As another characteristic related to risk preferences, we test the preference for insurance proxied by the holding of other SuppHIs except SuppDI ("*Preference for insurance*").[60] Examples for further SuppHIs in our data are a daily sickness or hospital daily benefits insurance and a supplemental hospital insurance covering the treatment by chief physician and a single or double hospital bed.[61] Based on de Meza and Webb (2001), we argue that people holding many SuppHIs buy SuppDI because of their inner need for security and their

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[60] The holding of several SuppHIs can basically be driven by the individual's preference for insurance coverage and by supplier behavior. However, to the best of our knowledge, insurance companies do not offer discounts for individuals buying more than one SuppHI. Moreover, the share of SHI enrollees with one specific type of SuppHI varies substantially. For instance, many SHI enrollees with a SuppDI do not hold a supplemental hospital insurance (Grabka, 2014). Thus, in line with Browne and Zhou-Richter (2014), we suggest that the holding of several SuppHIs is more likely to be driven by the individual's preference for insurance.

[61] Further examples are a SuppHI with benefits for eyeglasses, drugs, and other medication, a CompLTCI, a SuppHI for alternative healing methods and naturopathy, a SuppHI for cures and special medical check-ups and a SuppHI for treatment by a private physician.

generally higher preference for insurance on the one hand and are more likely to take precautions leading to lower ex-post risk on the other hand.[62]

Based on classical adverse selection models (e.g., Rothschild & Stiglitz, 1976) and empirical findings (e.g., Browne & Zhou-Richter, 2014) we examine self-rated health as a potential source of adverse selection. The rationale is that people with private information about their bad health are more likely to expect future dental treatments and are more likely to buy SuppDI. We measure self-assessed health by a categorical variable ("*Self-rated health"*) with 1 for bad health to 5 for excellent health. Finally, we test socioeconomic characteristics, including income ("*Income*"), employment (e.g., "*Full time*"), marital status ("*Married*") household size ("*HH size*") and education ("*A-level*") as potential drivers for selection. Based on previous findings (e.g., Buchmueller et al., 2013; Fang et al., 2008), we suggest that a better socioeconomic status, such as higher income, contributes to advantageous selection in the SuppDI market.

4.5 Results

4.5.1 Evidence of Heterogeneous Selection

We first analyze the data using the two aforementioned approaches to test for asymmetric information in insurance markets. Table 4.2 summarizes the results of the one- and two-equation approach using different estimation techniques. Regressing dental risk on the dummy for holding SuppDI (one-equation approach), while controlling for pricing characteristics, shows no significant difference between the groups both using a LPM and a probit estimation (column 1 and 2). Similarly, for the two-equation approach, we do not find a significant correlation between the residuals obtained from the two regressions of risk and insurance demand on pricing characteristics. This holds both when using a bivariate probit model (column 3) and when checking the independence of the residuals after estimating equation (2) and (3) separately by a LPM (column 1) and a probit model (column 2).

[62] Note that empirical evidence (e.g., Chen & Hunter, 1996; Lang, Farghaly, & Ronis, 1994; Levin & Shenkman, 2004) shows that dental prevention, such as periodic dental check-ups or flossing, is predominantly positively related to dental health. See Petersen (2003), for instance, for a discussion on oral disease prevention.

Table 4.2: Coverage-Risk Correlation

Dependent Variable	Dentist visits > 2		
	(1) LPM	(2) Probit	(3) Biprobit
Coefficient from regression of dentist visits on SuppDI	0.0246 (0.022)	0.1118 (0.097)	
Observations	1,474	1,375	
Correlation coefficient of residuals $\rho\ (\varepsilon, \eta)$	0.0316 (p = 0.225)	0.0304 (p = 0.261)	0.0658 (p = 0.258)
Observations	1,474	1,375	1,474

Notes: The residuals are derived from equation (2) and (3). Since we additionally control for vector *C* in equation (2), which leads to few missing values, the slightly different number of observations between the regressions of the two equations was aligned. The coefficient in column (2) represents the correlation between predicted Pearson residuals. In column (3), the correlation coefficient is based on a bivariate probit model. The coefficients for the pricing characteristics are not displayed in this table due to the high number of interaction terms. Robust standard errors for the coefficient from the regression of dentist visits on SuppDI and p-values for the correlation coefficient of the residuals in parentheses, respectively. *p < 0.10, **p < 0.05, ***p < 0.01.

Based on these results, one could conclude the absence of asymmetric information in the German market for SuppDI. Since this finding can, however, also be explained by an offsetting of adverse and advantageous selection in the aggregate, we exploit the rich data set and test for sources of selection. Table 4.3 shows the results for adding each potential driver for selection separately (column 1 and 2) and adding those potential drivers simultaneously (column 3 and 4) to our basic bivariate probit model. Here, we cluster our variables along two main categories: first, a set of factors related to risk preferences and, second, socioeconomic characteristics including self-rated health. Among the attributes related to risk preferences, we only find that preference for insurance significantly and positively correlates with the demand for SuppDI, but negatively with dental risk. To interpret preference for insurance as a driver for selection in the SuppDI market, the issue of causality in the relationship of preference for insurance with SuppDI and risk is important. If the risk covered by any SuppHI except SuppDI correlates with the number of dentist visits through other ways than the link of risk aversion, our estimates would be biased. Admittedly, we doubt that worse dental health is likely to influence the decision to buy one of the other SuppHI products. Moreover, other health issues that increase the likelihood of other SuppHIs, such as supplemental hospital insurance, may not affect dental care, being a very distinct field. Nevertheless, if an individual's general health correlates negatively with overall insurance coverage and positively with dental health, any potential bias is likely to be positive. The relationships of preference for insurance with our dependent variables remain robustly significant when we control for further covariates, including overall health, in column 3 and 4.

Furthermore, the correlation of the residuals turns from insignificant (Table 4.2) to significantly positive when controlling for this attribute. In line with Browne and Zhou-Richter (2014), these findings indicate that preference for insurance is a source of advantageous selection. Consistent with Srivastava et al. (2017), we find that individuals with higher income are more likely to hold a SuppDI and tend to go more often to the dentist for acute treatment. However, this only holds if we estimate all the covariates jointly. This finding indicates that income rather contributes to an adverse selection in this market. Self-rated health correlates as expected significantly negatively with dental risk, but the correlation with the holding of SuppDI is insignificant. This finding does not support the prediction that self-assessed health is a source of adverse selection in this market. The correlation coefficient of the bivariate probit model after controlling for all potential drivers for selection ($\rho\ (\varphi, \phi) = 0.1379$**) suggests that there are still unobserved characteristics that correlate positively with insurance demand and dental risk and hence offset the advantageous selection driven by preference for insurance.

Table 4.3: Sources of Selection

	(1)	(2)	(3)	(4)	(5)
	Adding potential sources separately			Adding all potential sources simultaneously	
	DentVisits	SuppDI	$\rho\ (\varphi, \phi)$	DentVisits	SuppDI
Risk preferences					
Care about health	-0.0495	0.0184	0.0642	-0.0604	-0.0763
	(0.061)	(0.050)	(p = 0.270)	(0.069)	(0.062)
Never smoker	0.0505	-0.0425	0.0628	-0.0026	-0.0071
	(0.094)	(0.077)	(p = 0.284)	(0.101)	(0.090)
BMI	-0.0122	0.0005	0.0591	-0.0125	-0.0122
	(0.011)	(0.007)	(p = 0.314)	(0.011)	(0.008)
Physical activity	-0.0409	0.0293	0.0661	-0.0395	-0.0008
	(0.029)	(0.024)	(p = 0.257)	(0.031)	(0.029)
Fruits	0.0141	0.0616	0.0637	0.0026	0.0495
	(0.058)	(0.048)	(p = 0.274)	(0.066)	(0.062)
Vegetables	0.0228	0.1445**	0.0634	0.0432	0.0310
	(0.069)	(0.057)	(p = 0.278)	(0.079)	(0.073)
Fast food	-0.0367	-0.0024	0.0798	-0.0477	0.0175
	(0.076)	(0.066)	(p = 0.174)	(0.081)	(0.078)
Sweets	0.0512	0.0204	0.0728	0.0485	0.0318
	(0.058)	(0.049)	(p = 0.213)	(0.064)	(0.057)
Preference for insurance	-0.1162**	0.7795***	0.1446**	-0.1372***	0.7471***
	(0.049)	(0.056)	(p = 0.020)	(0.051)	(0.057)
Socioeconomic characteristics					
Employment			0.0657		
			(p = 0.259)		
Part time work	0.0365	-0.1902		0.0954	-0.0686
	(0.154)	(0.129)		(0.164)	(0.153)
Hourly based work	-0.0352	-0.0564		-0.0765	0.0296
	(0.214)	(0.173)		(0.239)	(0.206)
Unemployed	-0.1346	-0.0801		-0.1249	-0.0520
	(0.155)	(0.128)		(0.171)	(0.153)
Job Training	-0.2060	-0.2908		-0.2796	-0.0368
	(0.301)	(0.266)		(0.328)	(0.285)
A-level	0.0520	-0.0844	0.0682	0.0201	-0.0941
	(0.090)	(0.076)	(p = 0.241)	(0.094)	(0.091)
Marital status			0.0592		
			(p = 0.314)		
Married	0.0353	0.3506***		0.1113	0.3003**
	(0.125)	(0.103)		(0.147)	(0.133)
Widowed	0.2227	0.3286		0.2688	0.2090
	(0.229)	(0.211)		(0.235)	(0.238)
Divorced	-0.1159	0.2187		-0.0674	0.4201**
	(0.194)	(0.156)		(0.202)	(0.174)
Income	0.0554	0.2061***	0.0547	0.0887*	0.1555***
	(0.041)	(0.036)	(p = 0.352)	(0.049)	(0.048)
HH size	-0.0461	0.0493	0.0658	-0.1143*	-0.0304
	(0.044)	(0.037)	(p = 0.259)	(0.061)	(0.055)
Health status					
Self-rated health	-0.1379**	-0.0034	0.0659	-0.1736**	-0.0717
	(0.063)	(0.049)	(p = 0.259)	(0.072)	(0.061)
Constant				-0.3560	-2.1415***
				(0.776)	(0.709)
Pricing Characteristics	Yes	Yes		Yes	Yes
Fear dummies	Yes	No		Yes	No
Preventive Visits	Yes	No		Yes	No
Observations				1,382	
Correlation between residuals $\rho\ (\varphi, \phi)$				0.1379** (p = 0.033)	

Notes: Income is measured in €1,000 intervals from < € 1,000 up to > €5,000 monthly net household income. Self-rated health: bad = 1 to excellent = 5. Care about health: not at all = 1 to very strongly = 5. Physical activity: never = 1 to daily = 6. Diet: never/seldom = 1 to daily = 4. Omitted reference categories: full time employment, marital status = single. The correlation coefficients of the residuals are based on a bivariate probit model. Robust standard errors for the coefficients and p-values for the correlation coefficient of the residuals in parentheses, respectively. *p < 0.10, **p < 0.05, ***p < 0.01.

In an additional test, we provide support for our assumption that people with a higher preference for insurance are better dental risks and, therefore, go to the dentist less often. We analyzed the share of individuals without any dental problems and the self-rated health for four separate subgroups. In Table 4.4, we report the differences in means within the first and last two columns. The first row shows that the share of individuals without SuppDI coverage (12.6%) who are not suffering from any dental problems is significantly higher than the respective share of SuppDI policyholders (8.9%). That indicates that SuppDI policyholders are higher risk types in the aggregate. To get a clearer picture on preference for insurance as a driver for advantageous selection, column 3 and 4 show a comparison of SuppDI policyholders with high (i.e., $>$ 2 additional SuppHIs) and low preference for insurance ($\leq$ 2 additional SuppHIs). 17.2% of SuppDI policyholders with high preference for insurance have no dental issues versus only 7.4% of SuppDI policyholders with low preference for insurance. This significantly lower result is consistent with our earlier estimations showing that multidimensional private information leads to advantageous selection by some individuals. People with a high preference for insurance seem to have better dental health, an observation supported by the fact that their mean of self-rated overall health is slightly higher than that of the comparison group.

Table 4.4: Differences by Insurance and Subgroup

	(1)	(2)	(3)	(4)
Variable	No SuppDI	SuppDI	≤ 2 other SuppHIs	> 2 other SuppHIs
No dental issues	0.126	0.089**	0.074	0.172**
Observations	1,067	429	365	64
Self-rated health	3.135	3.121	3.092	3.286*
Observations	1,059	423	360	63

Notes: Measurements: no dental issues (1 = yes); self-related health from bad (1) to excellent (5). The level of significance for the statistical differences in means in a two-sided *t*-test between the two groups in column (1) and (2) as well as between the groups in column (3) and (4) is designated as follows: *p < 0.10; **p < 0.05; ***p < 0.01.

4.5.2 Robustness Checks

The main results are based on distinct specifications of the risk proxy ($DentVisits$) and the proxy for preference for insurance ($Preference\ for\ insurance$) as the main driver for selection. To emphasize the robustness of our results, we test several different specifications of those variables and thereby assess the sensitivity of our main results. Table 4.5 presents how different specifications of the variable for dentist visits affect its correlation with the holding of SuppDI in the LPM and with preference for insurance in the bivariate probit model. The correlation between SuppDI and dentist visits remains insignificant when varying the cutoff for the dummy variable for dentist visits and controlling for the same set of covariates as in our basic LPM. However, for the linear specification, the coverage-risk estimate shows a positive and significant correlation between SuppDI and dentist visits at least on a 10% level, which might indicate the existence of moral hazard or adverse selection in the aggregate. Alternatively, the positive association could result from inadequately capturing some non-acute dentist visits of highly risk averse SuppDI policyholders, which is why we refrained from using this specification in our main model. In line with results from Table 4.3, when controlling for potential drivers, including preference for insurance, the association between SuppDI and dental risk becomes positively significant for most specifications. The correlation of dentist visits and preference for insurance remains robustly significant for some, but not all, other specifications of dentist visits. In column 8 of Table 4.5, we additionally use the dummy variable indicating no dental issues, already presented in Table 4.4, as an alternative risk proxy. Results are similar to dentist visits as we do not find a significant coverage-risk correlation. Moreover, people with a high preference for insurance are more likely to have no dental issues, i.e., they are more likely to be a low-risk type.

Table 4.6 shows the results of testing the sensitivity of the specification of our preference for insurance variable. Based on the bivariate probit model, we find that the results are quite robust when using a dummy variable for preference for insurance with different cutoffs. This supports our main findings shown in the previous section.[63]

[63] Testing for larger cutoffs for the variable *Preference for Insurance* results in cell sizes of less than ten observations.

Table 4.5: Sensitivity Test for the Specification of the Dependent Variable

Dependent Variable	Dentist visits							No dental issues
	(1) Cutoff > 0	(2) Cutoff > 1	(3) Cutoff > 2	(4) Cutoff > 3	(5) Cutoff > 4	(6) Cutoff > 5	(7) Linear	(8) Cutoff > 0
Independent Variable								
	LPM / OLS only controlling for underwriting and vector C							*without C*
	0.0357	0.0169	0.0246	0.0250	0.0207	0.0160	0.1873*	-0.0067
	(0.022)	(0.027)	(0.022)	(0.019)	(0.015)	(0.013)	(0.103)	(0.017)
SuppDI	*LPM controlling for underwriting, vector C + all potential drivers for selection*							*without C*
	0.0377	0.0558*	0.0492*	0.0349	0.0381**	0.0317**	0.3196***	-0.0239
	(0.025)	(0.032)	(0.027)	(0.022)	(0.018)	(0.016)	(0.121)	(0.019)
	Bivariate probit model controlling for underwriting and vector C							*without C*
	-0.0008	-0.0840**	-0.1162**	-0.0705	-0.1064	-0.1535**		0.1086*
	(0.041)	(0.039)	(0.049)	(0.059)	(0.067)	(0.076)		(0.059)
Preference for insurance	*Bivariate probit model controlling for underwriting, vector C + all potential drivers for selection*							*without C*
	0.0092	-0.0672*	-0.1372***	-0.1045*	-0.1402*	-0.1448*		0.1074*
	(0.043)	(0.041)	(0.051)	(0.061)	(0.073)	(0.079)		(0.060)

Notes: The list of all potential drivers of selection corresponds to the list of potential drivers used in Table 4.3. The number of observations slightly varies between the specifications due to missing values. The cells for the linear specification of dentist visits in the bivariate probit model are left blank as this model is based on binary dependent variables. Robust standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 4.6: Sensitivity Test for the Specification of Preference for Insurance

	Dentist visits > 2	
	(1)	(2)
Dependent Variable	Dentist visits > 2	SuppDI
Independent Variable	Preference for insurance	Preference for insurance
	Bivariate probit model controlling for underwriting and vector C	
Cutoff > 0	-0.1704*	1.2858***
	(0.101)	(0.084)
Cutoff > 1	-0.3592**	1.6034***
	(0.150)	(0.125)
Cutoff > 2	-0.5628**	1.9118***
	(0.238)	(0.226)
Linear	-0.1162**	0.7795***
	(0.049)	(0.056)
Observations	1,474	1,474
	Bivariate probit model controlling for underwriting, vector C + all potential drivers for selection	
Cutoff > 0	-0.1774*	1.2511***
	(0.106)	(0.089)
Cutoff > 1	-0.4231***	1.5096***
	(0.156)	(0.129)
Cutoff > 2	-0.6662***	1.8335***
	(0.253)	(0.229)
Linear	-0.1372***	0.7471***
	(0.051)	(0.057)
Observations	1,382	1,382

Notes: Potential drivers of selection correspond to the list of potential drivers used in Table 4.3. Robust standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

This analysis is based on survey data. The survey items about dental health, however, only capture their extensive margin, but do not allow differentiating the intensity of a specific dental issue. For instance, we can observe if a participant has at least one missing tooth or not but we do not observe how many teeth are actually missing. Thus, we cannot fully rule out a possible bias in the risk distribution in the overall market, as some insurers may reject applicants for SuppDI based on the intensity of their dental issues. Even though we know that rejections may occur due to missing teeth or dental prostheses, some insurers only reject applicants if the number exceeds a certain threshold, which cannot be identified in the data. To provide further insights into this potential problem, we split our sample and exclude all individuals that have at least one dental prosthesis, implant or missing tooth. Hence, similar to Finkelstein and McGarry (2006), we are able to test the coverage-risk correlation for a more homogeneous subsample of individuals as we can be certain that individuals in the remaining sample would not be rejected by insurers. Results in panel A of Table 4.7 support the non-significant relationship between dentist visits for acute treatments and SuppDI coverage. Similarly, preference for insurance remains a robust driver for advantageous selection (columns 3 and 4). The results in Panel B of Table 4.7 reveal that our findings for the alternative risk proxy, i.e., no dental issues, are similar to our findings for dentist visits (Panel A).[64]

Table 4.7: Coverage-Risk Correlation for Non-rejection Sample

Dependent Variable	Panel A: Dentist visits > 2			SuppDI
	(1)	(2)	(3)	(4)
	LPM	Probit	Biprobit	Biprobit
Independent variable				
SuppDI	0.0136	0.0703		
	(0.027)	(0.155)		
Preference for insurance			-0.1773*	0.7706***
			(0.096)	(0.077)
Observations	688	688	688	688
Dependent Variable	Panel B: No dental issues			SuppDI
	LPM	Probit	Biprobit	Biprobit
Independent variable				
SuppDI	-0.0141	-0.0506		
	(0.035)	(0.126)		
Preference for insurance			0.1092*	0.7616***
			(0.059)	(0.077)
Observations	702	702	702	702

Notes: As we only consider individuals without dental implants, dental prostheses or missing teeth, we only use age and gender to control for pricing characteristics. The coefficients for the pricing characteristics are not displayed in this table due to the high number of interaction terms. In Panel A, we use the number of dentist visits for acute treatment as a risk proxy and additionally control for vector *C*. In Panel B, the risk proxy is the dummy variable that indicates 1 if individuals do not have any dental issues and 0 otherwise. Robust standard errors in parenthesis *p < 0.10, **p < 0.05, ***p < 0.01.

4.6 Conclusions

In this paper, we analyze information asymmetry and related selection effects in the German SuppDI market. Applying the standard positive correlation test, our results provide no evidence that individuals with SuppDI are higher risk types than non-enrollees. Thus, in contrast to findings of Godfried et al. (2001), we find no support for the positive coverage-risk correlation in the aggregate as predicted by classic adverse selection models. Testing several potential sources of selection in a further step, we mainly identify the

[64] The use of the restricted sample resolves a second issue concerning the alternative risk proxy presented in Table 4.5 (column 8). Specifically, the variables for dental health that we use for risk classification (e.g., missing teeth) perfectly predict whether individuals have any dental issues. Even though these observations do not get omitted by our statistical software, results remain remarkably similar between the two approaches.

holding of other SuppHIs as a main driver for advantageous selection. This result remains robust even after we control for a comprehensive set of covariates. Our results suggest, however, that health-related behavior as another factor related to risk preferences, self-assessed health or socioeconomic characteristics only play a minor role with respect to selection effects in this market.

Overall, our findings provide solid evidence of information asymmetry in the German SuppDI market even though the coverage-risk correlation is not significantly different from zero. Following Finkelstein and McGarry (2006), we thus argue that more than one type of individual is buying SuppDI coverage: first, individuals with private information about their high risk (adverse selection) and second, low-risk individuals who purchase a SuppDI policy because of their preference for insurance (advantageous selection). It is important to note that such heterogeneous selection leads to a market equilibrium that is unlikely to be efficient (Finkelstein & McGarry, 2006). Hence, our results indicate that a shifting of dental insurance coverage from public insurance to a private insurance market may suffer from market inefficiencies due to suboptimal insurance coverage by at least some individuals.

Further research is needed that extends our insights about heterogeneous selection and tests our findings using longitudinal data with better measures for the risk of dental care expenditures and for risk preferences. Such investigation might give more insights into drivers for selection, which explains the remaining significant coverage-risk correlation even after controlling for a comprehensive set of covariates. In addition, it may help to understand better the causal channel by which risk preferences affect the risk of needing health or dental care. In the meantime, we suggest that insurance companies might gainfully use the selection effects identified here for a more thorough underwriting, which could decrease inefficiencies from information asymmetry. From an insurer's point of view, the selection effects could also be used to better attract low-risk individuals given that the German SuppDI market is not perfectly competitive.

5 The Effectiveness of a Population-Based Skin Cancer Screening Program: Evidence from Germany[65]

Abstract

In this paper, we analyze how a nationwide population-based skin cancer screening program (SCS) implemented in Germany in 2008 has impacted the number of hospital discharges following malignant skin neoplasm diagnosis and the malignant melanoma mortality rate per 100,000 inhabitants. Our panel data, drawn from the Eurostat database, cover subregions in 22 European countries, measured at the lowest nomenclature of territorial units for statistics (NUTS) level for 2000–2013. Applying fixed effects methods, we find a significantly positive and robust effect of the German SCS on the number of patients diagnosed with malignant skin neoplasm. However, the program does not significantly influence the melanoma mortality rate. This finding conflicts with the decreased melanoma mortality rate found for the pilot SCS program in northern Germany. Our results indicate that Germany's nationwide SCS program is effective in terms of a higher diagnosis rate for malignant skin neoplasms and thus may contribute to an improvement in the early detection of skin cancer.

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[65] This chapter is based on joint work with Micha Kaiser and Jörg Schiller both from the University of Hohenheim. The candidate's individual contribution focused on the literature review, data preparation, empirical analysis and the writing. The work was published by Springer Nature as 'Kaiser, M., Schiller, J. & Schreckenberger, C. (2018). The effectiveness of a population-based skin cancer screening program: evidence from Germany. *The European Journal of Health Economics*, *19*(3), 355–367. doi:10.1007/s10198-017-0888-4', and is used for this thesis with kind permission of Springer Nature. The work is available online: https://doi.org/10.1007/s10198-017-0888-4. The author wants to thank the anonymous reviewers for their valuable comments.

5.1 Introduction

The incidence of skin cancer, the most frequently diagnosed cancer, is increasing in many industrialized countries, including the U.S. and Germany (American Cancer Society, 2017; MacKie, Hauschild, & Eggermont, 2009; Robert Koch Institut und die Gesellschaft der epidemiologischen Krebsregister in Deutschland e. V., 2015; World Health Organization, 2016). In Germany, over 200,000 new cases of the commonest skin cancers – malignant melanoma (ICD–10 code C43), basal cell carcinoma, and squamous cell carcinoma (ICD–10 code C44), – were diagnosed in 2012. Moreover, although the mortality rate for malignant melanoma in Germany has remained relatively constant over the last 30 years, its age-standardized morbidity rate has more than tripled in the same time period. In 2012, over 20,000 individuals in Germany were diagnosed with malignant melanoma, and nearly 3000 died from this disease (Robert Koch Institut und die Gesellschaft der epidemiologischen Krebsregister in Deutschland e. V., 2015).

Skin cancer screening (SCS) may help to reduce morbidity and mortality from skin cancer by improved detection at an early stage (Breitbart et al., 2012; Choudhury, Volkmer, Greinert, Christophers, & Breitbart, 2012). In 2008, the German Statutory Health Insurance (SHI), which covers about 90% of the German population, introduced a nationwide population-based SCS program. This program is the first of its kind worldwide (Choudhury et al., 2012) and primarily aims at reducing melanoma mortality (Eisemann et al., 2015) and thus mitigating the related health care expenditures by an early identification of skin cancer (Stang et al., 2016). Under this program, SHI enrollees who are at least 35 years old are entitled to a whole body examination every 2 years (Geller et al., 2010). General practitioners and dermatologists are eligible to screen patients after completion of a standardized training program (Geller et al., 2010; Veit, Lüken, & Melsheimer, 2015). Additionally, since these screenings are free of charge, the insured are encouraged to check suspicious lesions as early as possible.

With respect to the effectiveness of the nationwide SCS program in Germany, a microsimulation of melanoma mortality in Germany predicted about a 45% reduction 20 years after the implementation of a biennial population-based SCS in 2008. More interestingly, this simulation predicts a relative decline of the mortality rate by about 14–17% 5 years after the implementation of a SCS program with a 2-year screening interval (Eisemann et al., 2015). An evaluation of the SCS program also documented a greater improvement in the malignant skin tumor detection rate in the first years after implementation than figures from previous years would have predicted (Veit et al., 2015).

As a basis for implementing the program nationwide, a research-based pilot project, Skin Cancer Research to Provide Evidence for Effectiveness of Screening in Northern Germany (SCREEN), was carried out in the federal state of Schleswig-Holstein in northern Germany between 2003 and 2004. Several studies have shown a substantial impact of this project on the incidence of melanoma and non-melanoma and on melanoma mortality (Breitbart et al., 2012; Eisemann et al., 2014; Katalinic et al., 2012; Waldmann et al., 2012). Waldmann et al. (2012), for instance, report that the incidence of melanoma increased during the SCREEN period compared to the pre-SCREEN period, while it decreased after this pilot project. Additionally, the results were compared with incident rates in the state of Saarland, where the pilot study was not conducted. The authors found that in Saarland the incidence rate only slightly increased between the pre- and post-SCREEN periods. Katalinic et al. (2012) identify an almost 50% decrease in melanoma mortality in Schleswig-Holstein between the pre-screening period (1998-1999) and 2008-2009, while the melanoma mortality rate in other German regions remained relatively constant over the same period. The findings of a study by Stang and Jöckel (2016), however, raised doubts about the SCS program's effectiveness in reducing the melanoma mortality rate based on the fact that incorrect assignment of some skin melanoma deaths could upwardly bias the rate recorded for SCREEN (Stang & Jöckel, 2016). This doubt is supported by other research evidence of a slight increase in melanoma mortality 5 years after SCS implementation in 2008 (Katalinic, Eisemann, & Waldmann, 2015; Stang & Jöckel, 2016). This research inconclusiveness echoes a similar ambiguity in earlier evidence of the benefits and efficacy of population-based SCS programs in reducing mortality or increasing the proportion of skin cancers detected at earlier stages (Choudhury et al., 2012; Federman, Kirsner, & Viola, 2013).

In this paper, we analyze the SCS's impact on the number of hospital discharges following a diagnosis of malignant skin neoplasm (ICD–10 code C43_C44) and the mortality rate from malignant melanoma (ICD–10 code C43) per 100,000 inhabitants. Our main research question is whether the national SCS program introduced in Germany in 2008 has been effective for these outcome variables. To answer this query, we empirically compare the regional skin cancer diagnosis and mortality rates for Germany with those for other European countries between 2000 and 2013. By applying a fixed effects model to panel data to assess the effects of the SCS program implementation on our outcome variables, we make a valuable contribution to the literature.[66] As far as we know, ours is the first study to use advanced panel data methods to analyze the effectiveness of a population-based SCS program. Our results contribute especially to the literature assessing the effectiveness of SCS programs.

5.2 Materials and Methods

Using Eurostat data for 22 European countries, we derive a valid proxy for SCS effectiveness by extracting hospital discharges by diagnosis (*diagnosis*) and causes of death (*mortality*) per 100,000 inhabitants. Because we are interested in skin cancer diagnosis and mortality, we focus on the diagnosis rate for malignant skin neoplasms (ICD–10 code C43_C44) and the mortality rates from malignant melanoma (ICD–10 code C43). We also obtain the following covariates from Eurostat: the proportion of individuals aged 65 and older (*age 65+*), the sex ratio (*sexratio*), the proportion with tertiary education (*educ*), the proportion of medical doctors per 100,000 inhabitants (*docdens*), the GDP per capita in logarithmic scale (*logGDP*), and employment rates (*employ*). All variables cover the same 2000–2013 time span except *mortality*, which covers only 2000–2012. The choice of our covariates is mainly based on the seminal work of Grossman (1972) which implies that the optimal choice of health investment is essentially influenced by the age, wealth and education of an individual (Grossman, 1972). Furthermore, past studies that evaluate socioeconomic risk factors of different cancer types tend to rely on a similar set of variables (Aarts, Lemmens, Louwman, Kunst, & Coebergh, 2010; Conway et al., 2015; Little & Eide, 2012). To obtain information about regional differences in the variables in our sample, we decompose every country into the lowest possible regional level indicated by the nomenclature of territorial units for statistics (NUTS) (Eurostat, 2016). As Table 5.1 shows, our final sample includes 1512 observations from 22 countries that are divided into 108 subregions.

[66] Since there was SCS in Schleswig-Holstein before the implementation of the nationwide SCS program in 2008, we take the SCREEN project in Schleswig-Holstein in two ways into account. While we exclude Schleswig-Holstein in the descriptive statistics, we consider this project in our empirical model.

Table 5.1: Number of Subregions and Observations by Country

Country	Subregions	Observations
Austria	9	126
Belgium	1	14
Bulgaria	1	14
Switzerland	1	14
Czech Republic	8	112
Germany	16	224
Denmark	1	14
Spain	18	252
Finland	1	14
France	22	308
Croatia	1	14
Hungary	1	14
Ireland	1	14
Italy	19	266
Netherlands	1	14
Norway	1	14
Poland	1	14
Portugal	1	14
Romania	1	14
Sweden	1	14
Slovenia	1	14
Slovakia	1	14
$\sum \mathbf{Countries} = 22$	$\sum \text{Regions} = 108$	$\sum \text{Observations} = 1512$

A comparison of the descriptive statistics of Europe and Germany (excluding Schleswig-Holstein) given in Table 5.2 shows that, on average, the ratio of males to females, i.e., the sex ratio, is almost the same in Europe and Germany. Furthermore, the density of medical doctors is nearly the same in Europe and in Germany, whereas the GDP per capita, employment rate, tertiary education rate, and proportion aged 65+ tend to be lower for non-German regions. The same holds true for both the average number of skin cancer diagnoses (*diagnosis*) and the average melanoma mortality rate (*mortality*). Expressed in percentages, the differences in *diagnosis* and *mortality* per 100,000 inhabitants between Germany and other European countries are about 125% (99.74 vs 44.42) and about 5% (3.00 vs 2.87), respectively.

Table 5.2: Summary Statistics for Europe and Germany

Variable	Europe (excluding Germany) Obs.	Mean (SD)	Min	Max	Germany (excluding Schleswig-Holstein) Obs.	Mean (SD)	Min	Max
age 65+ (in %)	1287	17.365 (3.049)	10.8	27.7	210	19.436 (2.288)	14.2	24.7
sexratio	1288	0.954 (0.025)	0.886	1.051	210	0.9572 (0.011)	0.930	0.983
docdens (no. per 100,000)	1245	366.159 (109.080)	192.653	976.253	210	366.406 (63.352)	259.073	588.665
GDP (in euros)	1288	23,585.02 (10,090.5)	1800	79,000	210	28,269.05 (8834.7)	15,800	54,600
educ (in %)	1286	20.831 (8.345)	6.5	46.8	210	26.175 (4.573)	15.3	37.2
employ (in %)	1286	68.628 (6.262)	46.3	83.3	210	74.839 (3.654)	65.5	81.5
diagnosis (no. per 100,000)	1212	44.420 (37.044)	1.2	305	210	99.741 (27.293)	47.2	184.7
mortality (no. per 100,000)	1148	2.869 (1.010)	0.6	7.2	195	3.000 (0.686)	0.2	4.82

Notes: Sample size varies slightly within each variable because of missing values.

A more sophisticated representation of the diagnosis and mortality rate differences can be obtained from the time trends for both variables, represented in Figure 5.1 as 2000–2013 skin cancer-related hospital discharges for Europe versus Germany. Whereas the trends for Europe appear stable across the period, Germany shows not only a monotonically increasing pattern of hospital discharges (that begins to intensify around 2006), but also a higher number of diagnoses. Interestingly, this sharp increase in diagnosis rate starts a few years before SCS implementation, which is consistent with program evaluations documenting the highest increase in reported skin cancer cases between 2007 and 2008 (Veit et al., 2015). These different trends can also be seen in Table 5.3, which splits the sample into four subsamples. Here, the 84.88 mean value of diagnoses per 100,000 persons in German regions (excluding the federal state of Schleswig-Holstein) between 2000 and 2007 rises by about 41% to 119.56 between 2008 and 2013.[67] Compared with

[67] We excluded the federal state of Schleswig-Holstein from Germany due to the SCREEN project, which was carried out between 2003 and 2004. However, the mean values of *diagnosis* and *mortality* for Germany only slightly change when Schleswig-Holstein is included.

this substantial increase, the 7% rise in other European regions (from 50.53 to 53.97) seems paltry.

Figure 5.1: Trends in Skin Cancer-related Hospital Discharges per 100,000 Inhabitants from 2000 to 2013 (a) and in Malignant Melanoma Mortality Rates from 2000 to 2012 (b) for Europe (excluding Germany) and Germany (excluding Schleswig-Holstein)

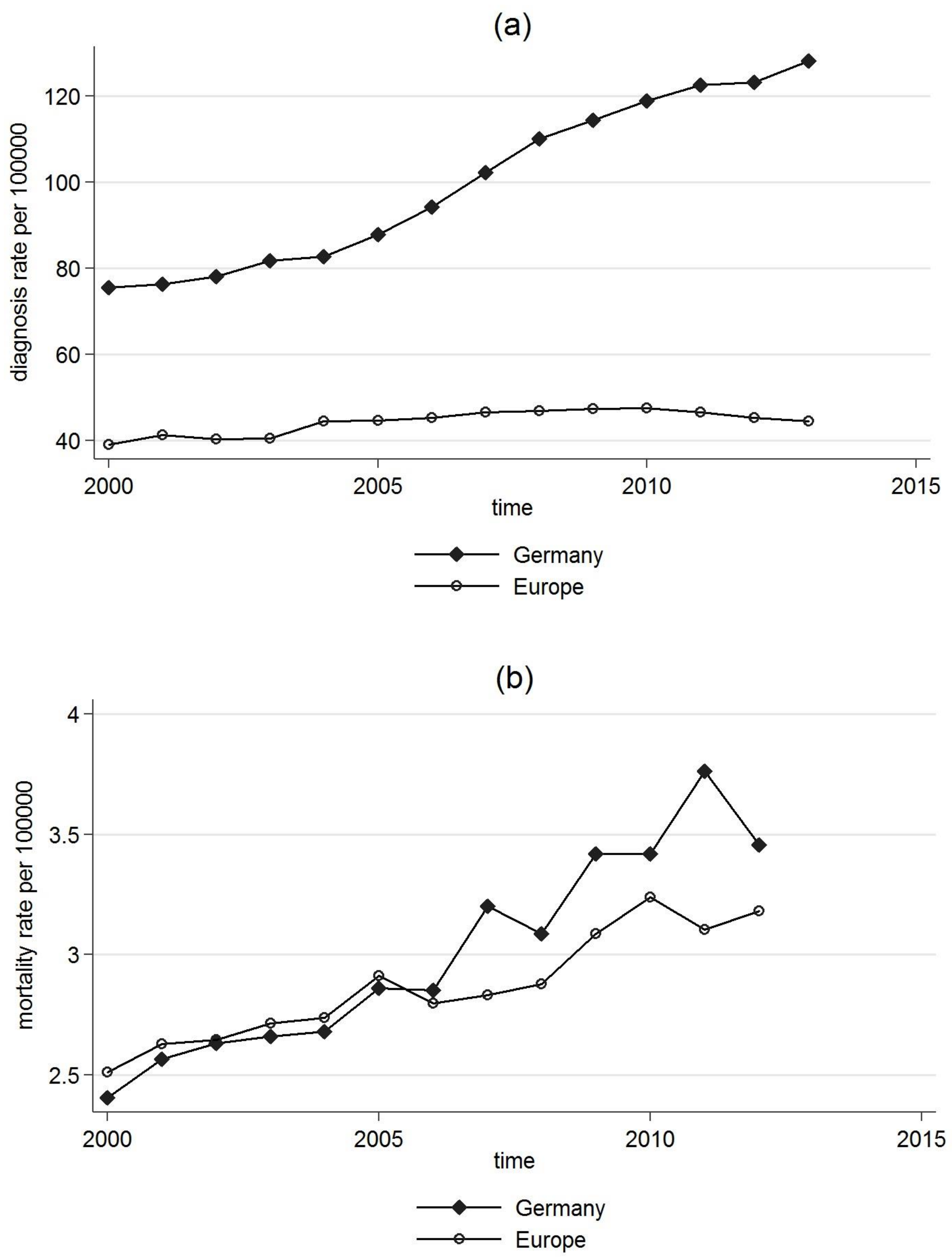


Table 5.3: Outcome Variables for Germany and Europe Before and After 2008

Outcome	2000–2007		2008–2013	
	Germany (excluding Schleswig-Holstein)			
	Observations	Mean (no. per 100,000)	Observations	Mean (no. per 100,000)
diagnosis	120	84.878	90	119.559
mortality	120	2.733	75	3.429
	Europe (excluding Germany)			
	Observations	Mean (no. per 100,000)	Observations	Mean (no. per 100,000)
diagnosis	805	50.532	673	53.969
mortality	791	2.841	614	3.155

Notes: The sample does not include data on mortality in 2013.

The 2000–2012 pattern of average melanoma mortality, in contrast, is similar in both Europe and Germany, with both lines in Figure 5.1 characterized by an overall increase. At the same time, the skin cancer mortality rate is slightly higher in Germany than in the other European regions. Considering the pre- (2000–2007) and post- (2008–2012) implementation periods separately, Table 5.3 shows about a 25% increase in *mortality* for Germany (from 2.73 to 3.43) but only a 10% increase for other European regions (from 2.84 to 3.12).[68] Admittedly, however, these descriptive differences in the dependent variables *diagnosis* and *mortality* (y_{it}) before ($T_{it} = 0$) and after SCS implementation ($T_{it} = 1$) do not address the hypothetical counterfactual of diagnosis and mortality trends in Germany had the program not been implemented. Hence, comparing the average outcomes of different German regions before and after SCS implementation leads to a selection bias and therefore to biased estimates (cf. Angrist & Pischke, 2009).

[68] A policy intervention, such as the implementation of the SCS program in Germany, may lead to special effects around the year of implementation. Hence, we additionally compared the means for the diagnosis and mortality rate between the time period between 2000-2007 and 2009-2013. The differences between these periods only slightly differ from our main specification of the time periods. Thus, we suggest that there are not any special effects around the year of implementation.

To circumvent this selection bias while measuring the SCS's effect on diagnoses and mortality rates, we set up a fixed effects model[69] that uses a hypothetical control group of all the European countries in our sample except Germany. For example, this method has been employed by Sabates and Feinstein (2006) to test education's effect on cervical cancer screening.[70] We estimate the impact of the SCS program on our outcome variables using the following model:

$$y_{it} = \alpha T_{it} + \beta X'_{it} + \gamma_i + \delta_t + u_{it} \qquad (1)$$

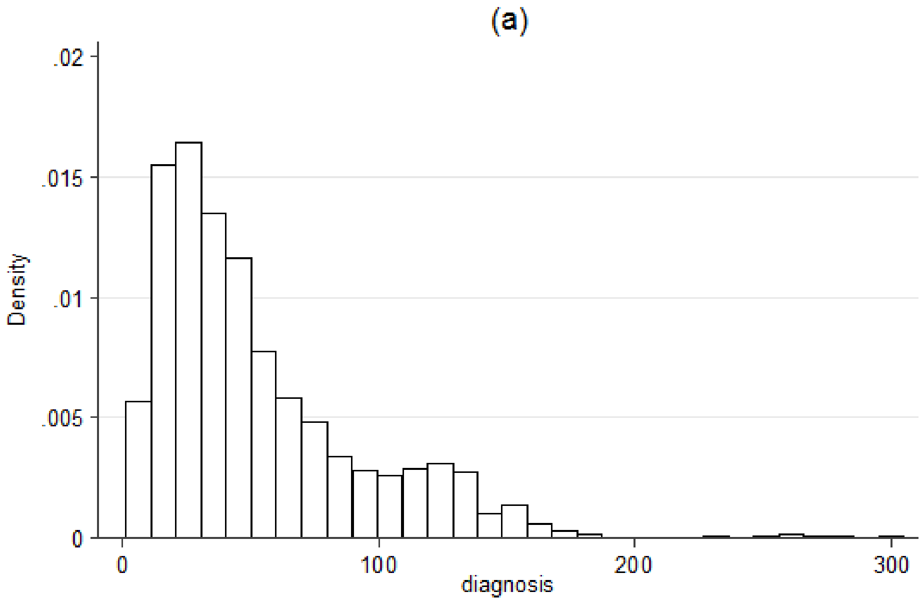
where y_{it} is either hospital discharges by *diagnosis* for skin neoplasms or *mortality* from melanoma per 100,000 inhabitants in subregion *i* in year *t.* As Figure 5.2 shows, *mortality* seems to be normally distributed, while *diagnosis* is skewed to the right. We therefore use a negative binomial fixed effect for *diagnosis* as the dependent variable. The treatment[71] variable T_{it} is a dummy equal to 1 if subregion *i* had a SCS program in year *t* (i.e., it is 1 for German subregions only) and 0 otherwise. We also consider the SCREEN pilot by assigning the value 1 to this variable for Schleswig-Holstein in 2003 and 2004. X'_{it} is a $1 \times N$ vector of covariates with additional information about certain characteristics of region *i* in year *t.* To control for unobserved but constant regional heterogeneity and for heterogeneity among the different time periods, we include dummies for regional (γ_i) and annual (δ_t) fixed effects.

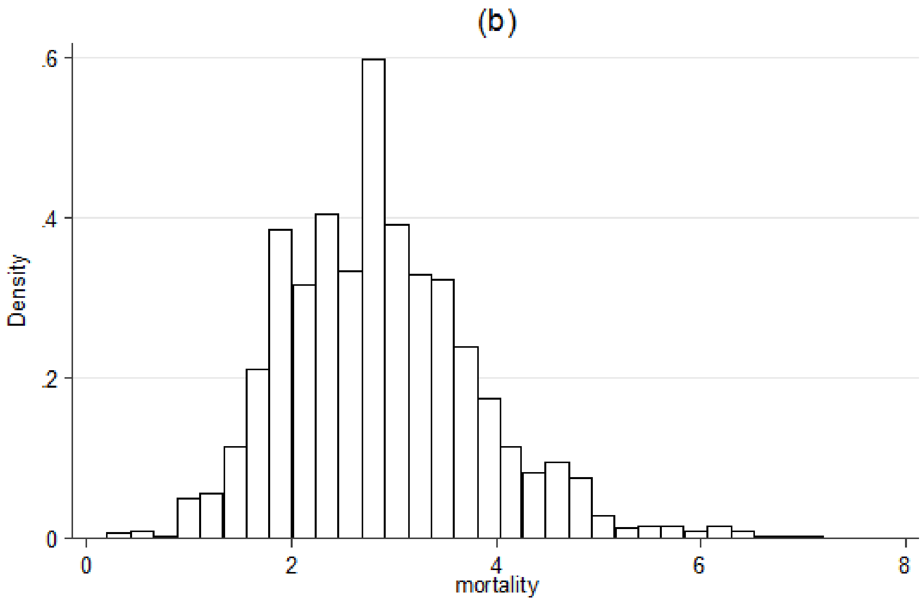
[69] Since we reject the null hypothesis of the Hausman specification test, we use a fixed effect instead of random effect technique in our model. In addition, we use a negative binomial fixed effect for *diagnosis* as dependent variable, since we can reject the null hypothesis of the Kolmogorow-Smirnow test for an underlying normal distribution. Moreover, we can reject the null hypothesis of a zero value of alpha by a likelihood-ratio χ^2 test, which suggests overdispersion of the data. Hence, a negative binomial model is superior to a Poisson model.

[70] Cf. Angrist and Pischke (2009) or Wooldridge (2013) for the mechanisms underlying fixed effects regression techniques.

[71] In this paper, the term "treatment" generally refers to the implementation of the German SCS program and the SCREEN pilot program in Schleswig-Holstein. To avoid any confusion from the difference between the SCS program implementation as a treatment effect in our empirical model and a medical treatment of skin cancer, we will explicitly call the latter "medical treatment".

Figure 5.2: Distribution of Skin Cancer-related Hospital Discharges per 100,000 Inhabitants (a) and of Malignant Melanoma Mortality Rates (b)





5.3 Results

Table 5.4 shows the impact of Germany's SCS program on our outcome variables using the fixed effects model in equation (1). The coefficient of our treatment variable representing the SCS's effect on diagnosed cases of malignant skin neoplasm is significantly positive (0.276) in the base model without covariates (column 1a). This positive effect remains significant with the addition of the different covariates (columns 1a-5a) even though the coefficient declines to 0.181 in the full model (column 5a). The coefficient for the treatment dummy indicates that sub-regions which participated in the SCS program are characterized by an incidence-rate-ratio of about 1.2. Specifically, this means that the implementation of the SCS in Germany has caused an increase of 20% in the rate of diagnoses of malignant skin neoplasms compared to the hypothetical counterfactual scenario. Looking at our covariates, we find that physician density, employment rate and the GDP per capita are the greatest contributors to this decreasing treatment coefficient, with higher physician density, employment rate, and GDP per capita associated with more diagnoses of malignant skin neoplasms. Moreover, the sex ratio also positively correlates with the number of diagnoses, while a higher proportion of 65+ and tertiary educated individuals negatively affect the number of diagnoses.

With respect to the melanoma mortality rate, Table 5.4 shows that it is only significantly and positively correlated by the SCS program (*treatment*) in the base model (column 1b); once the covariates are added in, the relation is not significantly different from zero (column 2b–5b). These results indicate that the SCS did not significantly influence the malignant melanoma mortality rate between 2008 and 2012, meaning that we cannot confirm the finding of an increased melanoma mortality rate 5 years after SCS implementation (Katalinic et al., 2015; Stang & Jöckel, 2016). In contrast to the findings for diagnosis, mortality rate is significantly and positively linked only to the proportion of those aged 65+ and physician density and negatively associated with the employment rate.

Table 5.4: Effect of the German SCS on Hospital Discharges by Diagnosis for Malignant Skin Neoplasm and Malignant Melanoma Mortality Rate

	Dependent Variable									
	Hospital discharges by diagnosis per 100,000 inhabitants for malignant skin neoplasm (ICD–10 code C43_C44)					Malignant melanoma mortality rate (ICD–10 code C43) per 100,000 inhabitants				
	(1a)	(2a)	(3a)	(4a)	(5a)	(1b)	(2b)	(3b)	(4b)	(5b)
Treatment	0.276*** (0.02)	0.291*** (0.02)	0.219*** (0.02)	0.214*** (0.02)	0.181*** (0.02)	0.242** (0.08)	0.143 (0.09)	0.119 (0.09)	0.117 (0.09)	0.077 (0.10)
Proportion of individuals aged 65 and older (in %)		-0.004 (0.01)	0.004 (0.01)	-0.010 (0.01)	-0.023** (0.01)		0.048* (0.02)	0.046* (0.02)	0.046* (0.02)	0.094*** (0.03)
Sex ratio		7.548*** (1.11)	5.723*** (1.08)	6.130*** (1.07)	3.432** (1.05)		-1.047 (2.30)	-0.391 (2.26)	-0.340 (2.28)	4.034 (3.35)
Physician density (no. per 100,000)			0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)			0.000+ (0.00)	0.000+ (0.00)	0.001* (0.00)
Proportion of individuals (aged 25–64) with a tertiary education (in %)				-0.121*** (0.00)	-0.124*** (0.00)				-0.000 (0.01)	0.012 (0.01)
Employment rate (in %)					0.032*** (0.00)					-0.018+ (0.01)
Natural log of GDP per capita (in euros)					0.307*** (0.07)					0.030 (0.19)
Constant	4.454*** (0.12)	-2.595* (1.07)	-0.830 (1.05)	-0.668 (1.05)	-3.034** (1.12)	2.506*** (0.09)	2.710 (2.29)	1.948 (2.25)	1.894 (2.26)	-2.390 (3.47)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1436	1435	1397	1396	1396	1356	1355	1315	1314	1314

Notes: The treatment variable equals 1 for all German subregions as of 2008 and for the German federal state of Schleswig-Holstein in 2003 and 2004. For *diagnosis* as dependent variable, we counter the right-skewed distribution by using a negative binomial fixed effects model. Standard errors are in parentheses. +p < 0.1, *p < 0.5, **p < 0.01, ***p < 0.001.

To test the robustness of our results, we first apply a pooled regression model with the malignant skin neoplasms diagnostic rate as dependent variable[72] and the same co-variates as in equation (1). As shown in Table 5.5, the results using this model confirm our findings with respect to the effect of the SCS program. Moreover, we apply a difference-in-difference-in-difference technique in order to exclude any possible unmeasured confounding factors that are likely to affect the diagnosis for both malignant skin neoplasms (ICD–10 code C43_C44) and other neoplasms (ICD–10 code C00_D48), i.e. general risk factors for cancer, such as smoking behavior, diet or alcohol consumption. Besides considering the pre- and post-SCS implementation period for Germany and Europe, we also include the diagnosis of neoplasms other than malignant skin neoplasms. In Table B.1 presented in the Appendix, we sketch our difference-in-difference-in-difference approach. As reported in Table 5.6, our finding that the German SCS program significantly and positively affects the number of hospital discharges following malignant skin neoplasm diagnosis using the difference-in-difference-in difference technique confirms our result of our fixed effect estimation in Table 5.4.[73]

[72] The rationale used for basing our pooled regression model on a negative binomial distribution of *diagnosis* is equivalent to the rationale used for basing our fixed effect model on this distribution.

[73] Furthermore, we assume that any unobserved factors that could influence the diagnosis rate for malignant skin neoplasms do not systematically differ between 2000 and 2013. To assess this assumption, we re-estimated our fixed effect model for shorter time periods, as this should exclude much of any unobserved confounding factors (not presented in the paper). We still find a significantly positive effect of the SCS program on diagnoses for skin neoplasms if we only consider the time period between 2006 and 2010 as well as the time period between 2007 and 2009.

Table 5.5: Effect of the German SCS on the Outcome Variables using Pooled Regression

	Dependent Variable									
	Hospital discharges by diagnosis per 100,000 inhabitants for malignant skin neoplasm (ICD–10 code C43_C44)					Malignant melanoma mortality rate (ICD–10 code C43) per 100,000 inhabitants				
	(1a)	(2a)	(3a)	(4a)	(5a)	(1b)	(2b)	(3b)	(4b)	(5b)
Treatment	0.919***	1.165***	1.155***	1.188***	0.852***	0.279*	0.280+	0.251+	0.263+	-0.231
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.14)	(0.15)	(0.15)	(0.16)	(0.16)
Proportion of individuals aged 65 and older (in %)		-0.055*	-0.054*	-0.052*	-0.040+		0.004	0.012	0.012	0.014
		(0.03)	(0.03)	(0.03)	(0.02)		(0.02)	(0.02)	(0.02)	(0.02)
Sex ratio		-12.434***	-11.141***	-10.389**	-13.105***		-4.638	-4.145	-3.827	-7.222*
		(2.99)	(3.19)	(3.45)	(2.71)		(3.74)	(3.67)	(3.54)	(3.07)
Physician density (no. per 100,000)			0.001+	0.001+	0.001*			0.000	0.000	0.000
			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)
Proportion of individuals (aged 25–64) with a tertiary education (in %)				-0.008+	-0.031**				-0.003	-0.038***
				(0.01)	(0.01)				(0.01)	(0.01)
Employment rate (in %)					0.059***					0.079***
					(0.01)					(0.01)
Natural log of GDP per capita (in euros)					0.027					0.314*
					(0.12)					(0.15)
Constant	3.828***	16.515***	14.945***	14.343***	12.880***	2.507***	6.853+	6.103+	5.846+	1.336
	(0.07)	(2.88)	(3.06)	(3.24)	(2.73)	(0.09)	(3.65)	(3.61)	(3.50)	(3.88)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1436	1435	1397	1396	1396	1356	1355	1315	1314	1314

Notes: The treatment variable equals 1 for all German subregions as of 2008 and for the German federal state of Schleswig-Holstein in 2003 and 2004. For *diagnosis* as dependent variable, we counter the right-skewed distribution by using a negative binomial regression model. Standard errors are in parentheses. +p < 0.1, *p < 0.5, **p < 0.01, ***p < 0.001.

Table 5.6: Effect of the German SCS on the Hospital Discharges by Diagnosis per 100,000 Inhabitants for Malignant Skin Neoplasm using a Difference-in-difference-in-difference Technique

	Dependent Variable				
	Hospital discharges by diagnosis per 100,000 inhabitants for malignant skin neoplasm (ICD–10 code C43_C44)				
	(1)	(2)	(3)	(4)	(5)
Treatment	0.358***	0.324***	0.311***	0.312***	0.306***
	(0.02)	(0.02)	(0.11)	(0.02)	(0.02)
Proportion of individuals aged 65 and older (in %)		0.022***	0.022***	0.019***	0.015***
		(0.00)	(0.00)	(0.00)	(0.00)
Sex ratio		0.932*	0.195	0.160	-0.890*
		(0.38)	(0.39)	(0.38)	(0.39)
Physician density (no. per 100,000)			0.000***	0.000***	0.000***
			(0.00)	(0.00)	(0.00)
Proportion of individuals (aged 25–64) with a tertiary education (in %)				-0.002+	-0.003*
				(0.00)	(0.00)
Employment rate (in %)					0.008***
					(0.00)
Natural log of GDP per capita (in euros)					0.244***
					(0.03)
Constant	5.221***	4.048***	4.717***	4.844***	3.094***
	(0.05)	(0.37)	(0.38)	(0.38)	(0.43)
Year dummies	Yes	Yes	Yes	Yes	Yes
N	2872	2870	2794	2792	2792

Notes: The treatment variable equals 1 for all German subregions as of 2008 and for the German federal state of Schleswig-Holstein in 2003 and 2004. We counter the right-skewed distribution by using a negative binomial regression model. Standard errors are in parentheses. +p < 0.1, *p < 0.5, **p < 0.01, ***p < 0.001.

However, because of the right skewed distribution of *diagnosis*, we cannot exclude the possibility of inefficiently estimated coefficients of our fixed effects or pooled regression model. We therefore estimate a finite mixture model (FMM) that accounts for distribution heterogeneity (Deb, Gallo, Ayyagari, Fletcher, & Sindelar, 2011). As Table 5.7 shows, we confirm a positive effect of the SCS in subregions with a lower malignant skin neoplasm diagnosis rate (*component 1*), whereas the impact of the SCS program is, although still significantly positive, considerably smaller in subregions with a comparatively high rate (*component 2*).

Additionally, we apply a pooled OLS regression using the malignant melanoma mortality rate as the dependent variable and again identify a significantly positive effect of the SCS program in the base model (see column 1b, Table 5.5). We find no significant correlation between the implementation of the SCS program and the malignant melanoma mortality rate once all covariates are added into the model (column 5b, Table 5.5). These findings are consistent with our results of the fixed effects estimation in Table 5.4. Finally, we test for a "placebo effect" by applying the treatment variable in our model to Austria, which shows similar trends for both our outcome variables as well as for all covariates. Estimating our model as though Austria had also implemented an SCS program in 2008, however, yields no significant impact of the SCS program implementation on the diagnosis rate once all covariates are controlled for (see column 5a, Table 5.8). This finding indicates that although SCS implementation in Germany has affected the malignant skin neoplasm diagnosis rate, its implementation in Austria has had no such effect. Moreover, as Table 5.8 also shows, the association between the SCS program and malignant melanoma mortality rate in Austrian subregions is not significantly different from zero, even in the base model without covariates.

Table 5.7: Effect of the German SCS on Hospital Discharges by Diagnosis for Malignant Skin Neoplasms using FMM

	Dependent Variable									
	Component 1					*Component 2*				
	(1a)	(2a)	(3a)	(4a)	(5a)	(1b)	(2b)	(3b)	(4b)	(5b)
Treatment	1.244***	1.408***	1.468***	1.446***	1.611***	0.181	0.245+	0.157+	0.192*	0.379***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.12)	(0.12)	(0.14)	(0.08)	(0.08)	(0.07)
Proportion of individuals aged 65 and older (in %)		-0.048***	-0.035***	-0.042***	-0.053***		-0.028+	-0.001	0.050***	-0.001
		(0.01)	(0.01)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)
Sex ratio		-12.313***	-10.544***	-11.957***	-15.513***		-7.303**	8.740***	14.422***	-9.750***
		(0.83)	(1.08)	(1.25)	(1.31)		(2.29)	(2.08)	(1.73)	(1.42)
Physician density (no. per 100,000)			-0.000	-0.000	-0.000			0.004***	0.005***	0.002***
			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)
Proportion of individuals (aged 25–64) with a tertiary education (in %)				0.000	-0.020***				-0.041***	-0.043***
				(0.00)	(0.09)				(0.00)	(0.00)
Employment rate (in %)					0.039***					0.063***
					(0.01)					(0.00)
Natural log of GDP per capita (in euros)					-0.107					0.063
					(0.10)					(0.05)
Constant	3.512***	16.179***	14.214***	15.770***	17.926***	4.582***	12.119***	-5.254*	-11.084***	8.774***
	(0.05)	(0.85)	(1.13)	(1.26)	(1.69)	(0.08)	(2.16)	(2.10)	(1.70)	(1.54)
Year dummies	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
N	1436	1435	1397	1396	1396	1436	1435	1397	1396	1396

Notes: The treatment variable equals 1 for all German subregions as of 2008 and for the German federal state of Schleswig-Holstein in 2003 and 2004. We counter the right-skewed distribution of *diagnosis* by using a negative binomial distribution in both components. Standard errors are in parentheses. +p < 0.1, *p < 0.5, **p < 0.01, ***p < 0.001.

Table 5.8: Placebo Effects of Applying the Treatment Variable to Austrian Subregions (Fixed Effects Model)

	Dependent Variable									
	Hospital discharges by diagnosis per 100,000 inhabitants for malignant skin neoplasm (ICD–10 code C43_C44)					Malignant melanoma mortality rate (ICD–10 code C43) per 100,000 inhabitants				
	(1a)	(2a)	(3a)	(4a)	(5a)	(1b)	(2b)	(3b)	(4b)	(5b)
Treatment2	0.160***	0.123***	0.042+	0.034	0.017	0.105	0.043	-0.003	0.009	0.011
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)
Proportion of individuals aged 65 and older (in %)		0.035***	0.037***	0.026***	0.005		0.089***	0.088***	0.099***	0.104***
		(0.01)	(0.01)	(0.01)	(0.01)		(0.02)	(0.02)	(0.02)	(0.02)
Sex ratio		6.362***	4.533***	4.913***	2.168*		1.261	2.169	2.256	3.960
		(1.15)	(1.09)	(1.10)	(1.07)		(3.01)	(3.18)	(3.18)	(3.35)
Physician density (no. per 100,000)			0.001***	0.001***	0.001***			0.001*	0.001*	0.001*
			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)
Proportion of individuals (aged 25–64) with a tertiary education (in %)				-0.009**	-0.010**				0.011	0.013
				(0.00)	(0.00)				(0.01)	(0.01)
Employment rate (in %)					0.037***					-0.017+
					(0.00)					(0.01)
Natural log of GDP per capita (in euros)					0.284***					-0.019
					(0.07)					(0.19)
Constant	4.144***	-2.215*	-0.387	-0.372	-2.735*	2.512***	-0.142	-1.229	-1.691	-2.488
	(0.11)	(1.11)	(1.07)	(1.07)	(1.16)	(0.05)	(2.96)	(3.08)	(3.12)	(3.47)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1436	1435	1397	1396	1396	1356	1355	1315	1314	1314

Notes: The treatment2 variable equals 1 for all Austrian subregions as of 2008. For *diagnosis* as the dependent variable, we use a negative binomial fixed effects model. Standard errors are in parentheses. +p < 0.1, *p < 0.5, **p < 0.01, ***p < 0.001.

5.4 Conclusions

This analysis of the effectiveness of Germany's nationwide population-based SCS program identifies a significant, robust effect of the SCS program on the number of malignant skin neoplasm diagnoses per 100,000 people. This finding is consistent with earlier reports of a positive effect of the SCREEN project and the national SCS program in Germany on the melanoma and non-melanoma incidence (Breitbart et al., 2012; Eisemann et al., 2014; Waldmann et al., 2012). It should be noted, however, that patients diagnosed with ICD–10 code C44 skin cancers are often ambulatory (Robert Koch Institut und die Gesellschaft der epidemiologischen Krebsregister in Deutschland e. V., 2015), meaning that the SCS's impact on the diagnosis rate could be higher than that recorded here for inpatient discharges.[74] Nevertheless, once we control for the different covariates, we identify no significant program effect on the melanoma mortality rate, so our findings fail to support prior evidence of a decreasing melanoma mortality produced by SCREEN (Breitbart et al., 2012; Katalinic et al., 2012). Furthermore, we cannot confirm the 14–17% decline of the malignant melanoma mortality rate in Germany 5 years after the implementation of the national biennial SCS, predicted in the microsimulation model of Eisemann et al. (2015).

The insignificant effect on the mortality rate may be partly explained by the complexity of determining the cause of death, which could bias disease-specific mortality rates (Black, Haggstrom, & Welch, 2002). Furthermore, the analysis is based on aggregate data, which do not allow us to control for individual skin cancer risk characteristics such as solarium attendance, sunburn prevention behavior, skin type, and/or existing moles. Furthermore, because our data cover comparatively few post-SCS periods, our results may not capture possible long-run effects on the mortality rate. On the other hand, while

[74] Both melanoma and non-melanoma skin cancer are more likely diagnosed by outside hospital services. Our data include information about the hospital discharges by diagnosis per 100,000 inhabitants for malignant skin neoplasm. It is fair to say that the number of these discharges include both the cases solely diagnosed in hospitals and cases already diagnosed by outside hospital services which are transferred to a hospital for treatment. The latter are also reported as hospital discharges by diagnosis per 100,000 inhabitants for malignant skin neoplasm. However, our data does not include cases that were diagnosed and solely treated by outside hospital services. Hence, our finding of a positive effect of Germany's SCS program on the malignant skin neoplasm diagnosis rate may underestimate the true effect.

Welch and Black (2010) suggest that an increasing diagnosis rate combined with no significant change in mortality rate may indicate skin cancer overdiagnosis,[75] such a finding could also be explained by a rising number of erroneously diagnosed benign skin lesions (Carli et al., 2003).[76]

Overall, our results indicate that Germany's nationwide population-based SCS program has been effective in terms of a higher diagnosis rate for malignant skin neoplasms and thus may have helped improve early detection of skin cancer. Future research on SCS effectiveness might consider extending our analysis by using longer time periods and individual data. Moreover, the German SCS program could additionally be evaluated in terms of process outcomes, such as the awareness of individuals for SCS and skin cancer prevention, improved quality of diagnosis among physicians or the acceptability among patients for SCS. Finally, a cost-effectiveness analysis should also be conducted to identify the extent to which prior findings on the cost-effectiveness of melanoma screenings can be confirmed for Germany's SCS program (Losina et al., 2007). In addition to assessing the justifiability of associated costs, such an analysis would provide reliable insights for policy decisions.

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[75] Welch, Woloshin, and Schwartz (2005), for instance, find evidence supporting melanoma overdiagnosis in the U.S. as a result of raised diagnostic scrutiny.

[76] A rising number of erroneously diagnosed benign skin lesions would lead to systematic measurement error, which we do not consider a major problem in our analysis.

6 General Conclusions

This dissertation contributes to the literature on effects of two different options which may help to reduce the financial burden on the public sector with respect to health and LTC expenditures and are thus of particular interest for governments in several OECD countries. The first option refers to the use of a voluntary private insurance system that provides coverage for gaps in a public LTCI or health insurance system. In particular, three academic papers contribute to the empirical literature of asymmetric information and selection effects in private LTCI and VPHI markets. An understanding of selection effects in these markets is useful for policy implications because they may indicate inefficiencies concerning the insurance coverage of individuals in a market of voluntary private insurance.

In a first step, chapter 2 reviews the empirical work on asymmetric information and related selection effects in markets for private LTCI and in the U.S. market for Medigap insurance. These types of insurance provide coverage for out-of-pocket LTC and health expenditure risks, which are of high importance for the elderly. The empirical literature shows that both adverse and advantageous selection are present in these insurance markets due to multidimensional private information. While the evidence suggests that advantageous selection is dominating in the U.S. Medigap insurance market, adverse and advantageous rather offset each other in the U.S. LTCI market. Only few empirical studies have analyzed selection effects in LTCI markets outside the U.S. and show mixed results with respect to the dominating selection effect. Concerning the sources of selection, some evidence on LTCI markets is consistent with classic models of asymmetric information (e.g., Rothschild & Stiglitz, 1976) by suggesting that adverse selection is driven by private information on the risk type. However, some results indicate that individuals who may actually have the opportunity to buy LTCI do not have significant private information on their risk type. Nevertheless, some studies suggest that the problem of adverse selection may arise or exacerbate due to a rising availability of genetic testing leading to increased private information. In line with theory (de Meza & Webb, 2001), some findings suggest that risk preferences contribute to advantageous selection in LTCI markets. However, advantageous selection in the Medigap insurance market is not mainly driven by risk aversion, but particularly by cognitive abilities. Moreover, some findings indicate that socioeconomic factors (e.g., income) that are not used for pricing by insurance companies may play an important role for selection effects. However, there is still need for further research on selection effects in these insurance markets to provide more profound policy implications. This includes extending the literature on selection behavior in LTCI markets other than the U.S. market, examining the channel through which some factors (e.g., cognitive abilities) impact selection effects and analyzing to what extent a negative coverage-risk correlation is supply-side or demand-side driven.

The subsequent chapters include two empirical studies that provide new insights on selection effects in the markets for CompLTCI and SuppDI in Germany. Both markets have in common that they provide voluntary private insurance coverage for residual out-of-pocket expenditure risks not covered by public LTCI or health insurance in Germany. In addition, the ex-ante premium differentiation is rather limited in these markets since risk-based premiums are only dependent on few characteristics. This makes these markets prone to selection effects.

Based on contract data on PHI policyholders of a German health insurance company, the results in Chapter 3 indicate that advantageous selection is dominating in the German CompLTCI market with respect to both the decision to buy a CompLTCI policy and to choose the extent of CompLTCI coverage. The occupation as well as the residential location are observable characteristics that are not used by the insurance company for pricing, but that contribute to advantageous selection through the socioeconomic status. Another unused observable that contributes to selection effects is the holding of further SuppHI policies even though the results concerning this factor as a source of either adverse or advantageous selection are mixed. In addition, the findings suggest that non-linearities in the relationship of potential sources of selection with risk and insurance coverage should be taken into account. Even though the insured collective is advantageously selected at a given point in time, findings of a panel data analysis point to a possible worsening of the insured collective over time. Individuals with increased health insurance payouts are more likely to buy CompLTCI, while policyholders with decreased health insurance payouts are more likely to cancel their CompLTCI contracts. Although it cannot be excluded that the latter points to an ex-post selection of low-risk individuals out of the collective, cancellations of CompLTCI policies are assumed to be rather driven by financial problems.

The empirical study on selection effects in the German market for SuppDI in Chapter 4 is based on survey data from the Healthcare Monitor of the Bertelsmann Stiftung. The findings provide evidence that asymmetric information and selection effects exist in this market even though the standard positive correlation test does not reveal a significant coverage-risk correlation. Analyzing several potential sources of selection, the holding of other private SuppHIs, which is related to risk preferences, is identified as a main source of advantageous selection. It can be concluded that the absence of a significant coverage-risk correlation is explained by an offsetting of adverse and advantageous selection in the aggregate. Thus, both high-risk individuals with private information on their risk type as well as low-risk individuals with private information on their preference for insurance purchase SuppDI.

The second option to reduce the financial burden on the public sector, which is analyzed in this thesis, refers to the promotion of preventive health measures. Specifically, Chapter 5 contributes to this topic by empirically analyzing the effectiveness of the nationwide population-based SCS program that was implemented in the German health care system in 2008. The purpose of this program is to lower the melanoma mortality rate and the costs of care by improving the detection of skin cancer at an early stage. Using panel data from the Eurostat database, the study shows a positive and robust effect of this program on the diagnosis rate for malignant skin neoplasms, but no significant impact on the melanoma mortality rate. Since the latter may partly be explained by the relatively short time period after the implementation of the program, future research might give more insights into long-term effects of this program on the melanoma mortality rate. The positive impact on the diagnosis rate suggests that this program may have improved the detection rate of skin cancer at an earlier stage and may thus help to mitigate the health care costs on skin cancer. However, taken the impact on the diagnosis rate and the melanoma mortality rate together, the findings may also indicate the problem of skin cancer overdiagnosis. The latter could even lead to rising health care costs related to skin cancer (e.g., Welch & Black, 2010).

Summing up, the results in this thesis point out some specific effects of shifting insurance coverage to a market for private LTCI and VPHI as well as of the promotion of preventive health care via a cancer screening program. In particular, the empirical results in this thesis suggest that selection effects due to multidimensional private information are present in the German market for CompLTCI and SuppDI, which is in line with findings for the Medigap insurance and the private LTCI market in the U.S. These findings raise the concern of inefficiencies in these insurance markets due to related suboptimal insurance coverage of at least part of the population. Hence, selection effects need to be addressed when considering the strategy of shifting coverage from a public LTCI or health insurance system to a private insurance market. Some evidence reviewed in this thesis suggest that inefficiencies in private insurance markets may be decreased by considering drivers for selection in determining insurance premiums. Instead of shifting insurance coverage to the private insurance market, an alternative way to lower the financial burden of the public sector is to promote preventive health care, for instance via a cancer screening program. In this regard, the findings in this thesis indicate that the German SCS program is effective in terms of a higher rate of malignant skin neoplasm diagnoses and may thus help to reduce the health care costs related to skin cancer by an early detection of that disease. However, future research on the cost-effectiveness of this specific screening program is needed to give more profound policy implications on the justifiability of the costs for this program.

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Appendix A

Table A.1: Specification of Variables

Variable	Explanation	Data Source
Risk		
LTCprob	1 = one or more insurance claims in the mandatory LTCI, 0 = otherwise	Insurance company
lnLTCcost	Natural log of insurance payouts in the mandatory LTCI + 1	Insurance company
HCprob	1 = one or more insurance claims in health insurance above the highest possible deductible, 0 = otherwise	Insurance company
lnHCcost	Natural log of insurance payouts in health insurance above the highest possible deductible + 1	Insurance company
Coverage		
CompLTCI	1 = holding of a CompLTCI, 0 = otherwise	Insurance company
lnCompLTCIp	Natural log of the monthly premium for CompLTCI tariffs + 1 (without rate module for increasing the benefits over time)	Insurance company
Pricing characteristics		
male	1 = man, 0 = woman	Insurance company
age	Age in years	Insurance company
year	Year of signing the insurance contract	Insurance company
Unused observables		
dsick_ins	1 = holding of a daily sickness benefits insurance, 0 = otherwise	Insurance company
dhosp_ins	1 = holding of a hospital daily benefits insurance, 0 = otherwise	Insurance company
ISEI-08	Socioeconomic status score based on ISEI-08	Assignment based on Ganzeboom and Treiman (2010)
educ_sec[a]	Proportion of individuals (aged 15 years and older) with the general / subject-restricted higher education entrance qualification per district (in %)	German Census 2011
employ	Employment rate (of individuals aged 15-64 years) per district (in %)	German Census 2011
gdp_10000	Average GDP per inhabitant by district between 2006 and 2013 (in 10,000 euros)	Eurostat
dependency ratio	Dependency ratio, i.e., the ratio of individuals aged under 18 years or 65 years and older to individuals aged 18-64 years per district (in %)	German Census 2011
single	Proportion of single adults (19 years and over) per district (in %)	German Census 2011
Further information of the insurance company		
LTCI_lapse	1 = lapse of CompLTCI policies, 0 = otherwise	Insurance company
distribution_dens	Proportion of distributors of CompLTCI policies per 10,000 inhabitants	Insurance company
tariff_non-payer	1 = holding of a “emergency treatments only” tariff for non-paying customers in financial distress, 0 = otherwise	Insurance company

Notes: [a] This educational degree in Germany is, for instance, the so called “Abitur” which is comparable to A-level in the U.K.

Table A.2: Marginal Effects on Health Insurance Benefits Before and After CompLTCI Lapse and Uptake

	(1)	(2)	(3)	(4)	(5)	(6)
	Lapse Behavior				Uptake Behavior	
Dependent variable	HCprob		lnHCcost		HCprob	lnHCcost
	Customers without financial distress	Customers in financial distress	Customers without financial distress	Customers in financial distress		
Before the event						
<= -5 years	0.5048***	0.4195***	3.8195***	3.2143***	0.3165***	2.3945***
	(0.035)	(0.040)	(0.268)	(0.299)	(0.007)	(0.053)
- 4 years	0.4147***	0.3366***	3.1182***	2.5523***	0.3066***	2.3016***
	(0.030)	(0.034)	(0.224)	(0.248)	(0.007)	(0.055)
- 3 years	0.4009***	0.3312***	3.0861***	2.6028***	0.2989***	2.2190***
	(0.027)	(0.029)	(0.207)	(0.217)	(0.006)	(0.047)
- 2 years	0.3704***	0.2901***	2.8163***	2.2444***	0.2957***	2.2040***
	(0.027)	(0.029)	(0.206)	(0.215)	(0.006)	(0.044)
- 1 years	0.4311***	0.2301***	3.2322***	1.7481***	0.3029***	2.2386***
	(0.028)	(0.027)	(0.218)	(0.200)	(0.005)	(0.039)
0	0.3790***	0.1163***	2.7921***	0.9148***	0.3516***	2.6098***
	(0.028)	(0.020)	(0.210)	(0.153)	(0.005)	(0.036)
After the event						
+ 1 year	0.3454***	0.1195***	2.6618***	0.9771***	0.3654***	2.7058***
	(0.029)	(0.024)	(0.232)	(0.183)	(0.005)	(0.038)
+ 2 year	0.2904***	0.0726***	2.2708***	0.6320***	0.3712***	2.7399***
	(0.032)	(0.020)	(0.256)	(0.175)	(0.005)	(0.040)
+ 3 year	0.3978***	0.0611***	3.1058***	0.5021***	0.3910***	2.9133***
	(0.036)	(0.019)	(0.297)	(0.150)	(0.006)	(0.045)
+ 4 year	0.4396***	0.1106***	3.4251***	0.8750***	0.3959***	2.9514***
	(0.042)	(0.031)	(0.344)	(0.251)	(0.006)	(0.047)
+ 5 year	0.4389***	0.0963**	3.4286***	0.7940**	0.4126***	3.1066***
	(0.062)	(0.039)	(0.506)	(0.340)	(0.005)	(0.043)
Pricing characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127,008				790,119	

Notes: Standard errors clustered on the level of the individual in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Appendix B

Table B.1: Difference-in-difference-in-difference Approach

	Malignant skin neoplasms ICD–10 code C43_C44	Neoplasms ICD–10 code C00_D48 (excluding ICD–10 code C43_C44)
	Germany	
$t < 2008$	x_G	y_G
$t > 2008$	$x_G{'}$	$y_G{'}$
Difference	$x_G{'} - x_G$	$y_G{'} - y_G$
Difference-difference	$\Delta\varphi_G = (x_G{'} - x_G) - (y_G{'} - y_G)$	
	Europe	
$t < 2008$	x_E	y_E
$t > 2008$	$x_E{'}$	$y_E{'}$
Difference	$x_E{'} - x_E$	$y_E{'} - y_E$
Difference–difference	$\Delta\varphi_E = (x_E{'} - x_E) - (y_E{'} - y_E)$	
Difference–difference–difference	$\Delta\varphi_G - \Delta\varphi_E$	