

# Essays in Empirical Health Economics

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Dipl.-Volksw. Christian Bünings

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Erstgutachter: Prof. Dr. Hendrik Schmitz  
Zweitgutachter: Prof. Dr. Stefan Felder

*To Franziska*

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# Chapter 1

## Introduction

### 1.1 Context and Scope

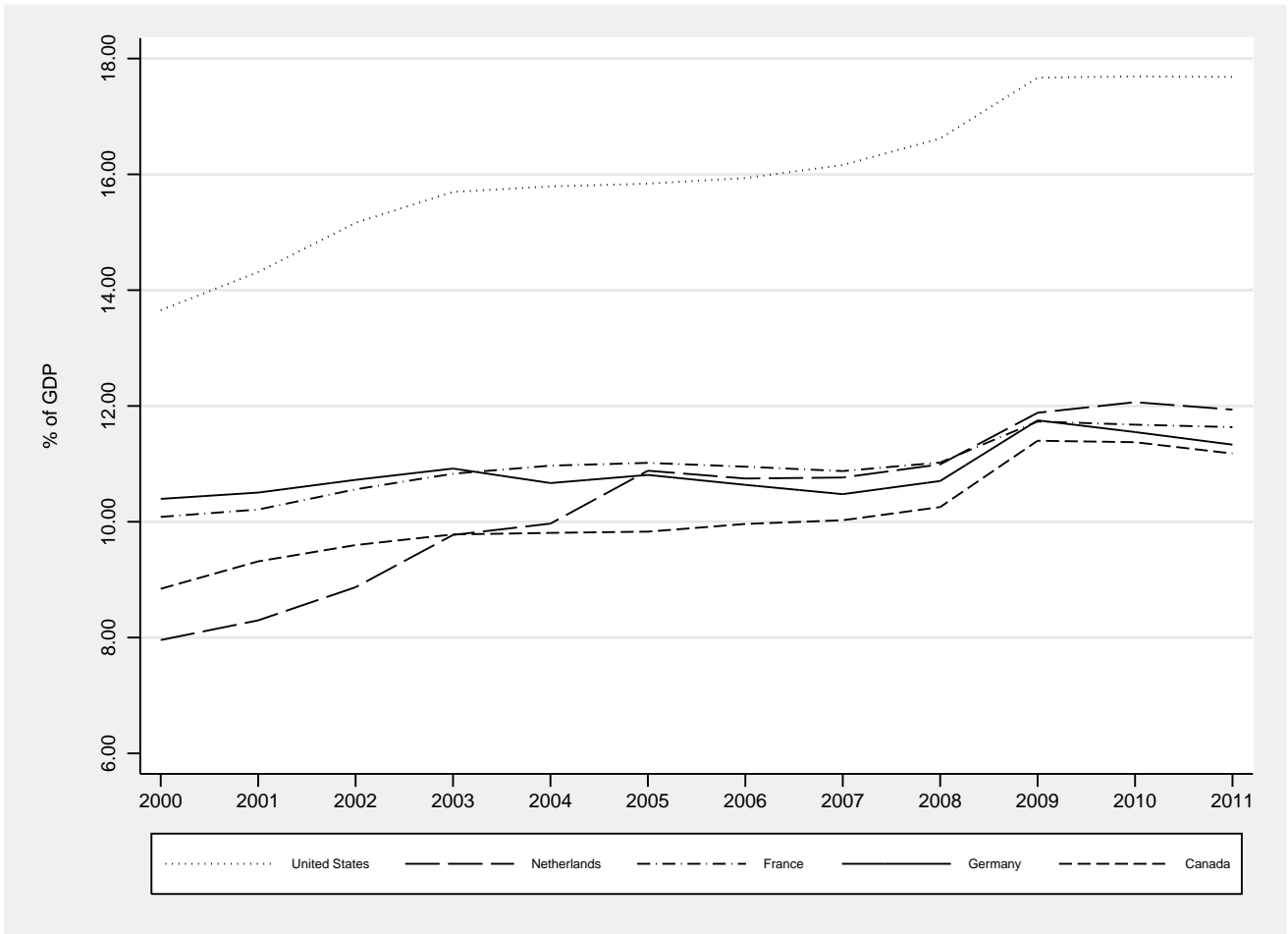
Health care expenditure (HCE) and its development have been subject to ongoing economic and political debates in many countries around the world over the last decades. In Germany, for instance, one prominent issue of such debates concerns potential labor market effects caused by rising HCE. Since the German health care system, which is characterized by universal coverage and almost equal access, is to a large extent government-funded ( $\approx 3/4$ ) through health insurance contributions that are mainly income-related and equally split between employer and employee, rising HCE may lead to increasing health insurance contribution rates and, hence, may also increase labor costs. Higher labor costs will – all else equal – lead to less employment, which will further increase pressure on public finance. In contrast to Germany, the health care system of the United States (U.S.) has a much stronger focus on private financing and, as a result, access is non-universal and unequal. In this context, political debates on HCE in the U.S. deal with, for instance, potential consequences for those who will not be able to afford the increasing health care premiums induced by rising HCE. Although the focus of such debates depends on the country and its health care system operated, most of these debates highlight the importance to gain control of the rising HCE.

To get a first quantitative impression of the volume of health spendings, Figure 1.1 shows the HCE in relation to GDP for the five OECD countries with the highest HCE in terms of GDP in 2011. As can be seen, the U.S. (dotted line) clearly outperform all other OECD countries in terms of HCE as share of GDP (17.7% in 2011). In Germany (solid line) HCE amount to around 294 bn € in 2011, which translates to 11.3 percent of GDP. The latter is similar to HCE in the Netherlands (11.9%), France (11.6%) and Canada (11.2%) in 2011. Although this can be considered as rather moderate as compared to the U.S., HCE in Germany are significantly above the average among OECD countries, which is 9.3 percent of the GDP (OECD, 2013). Apart from the absolute (relative) amount of HCE, a dominant topic of these debates concerns the development of HCE over time. While HCE represented 10.4 percent of the GDP in Germany in 2000, they amounted to 11.3 percent in 2011.<sup>1</sup> This is an increase by about one percentage point or around nine percent. The increase of HCE is even more dramatic in other OECD countries. For instance, HCE increased by around 26 and 29 percent in Canada and the U.S. respectively, and up to 50 percent in the Netherlands in the respective period. Understanding the determinants of HCE and

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<sup>1</sup>The peak in 2009 is rather attributable to a drop in GDP due to the economic crisis than to an increase in HCE.

Figure 1.1: Development of Health Care Expenditures in Selected OECD Countries

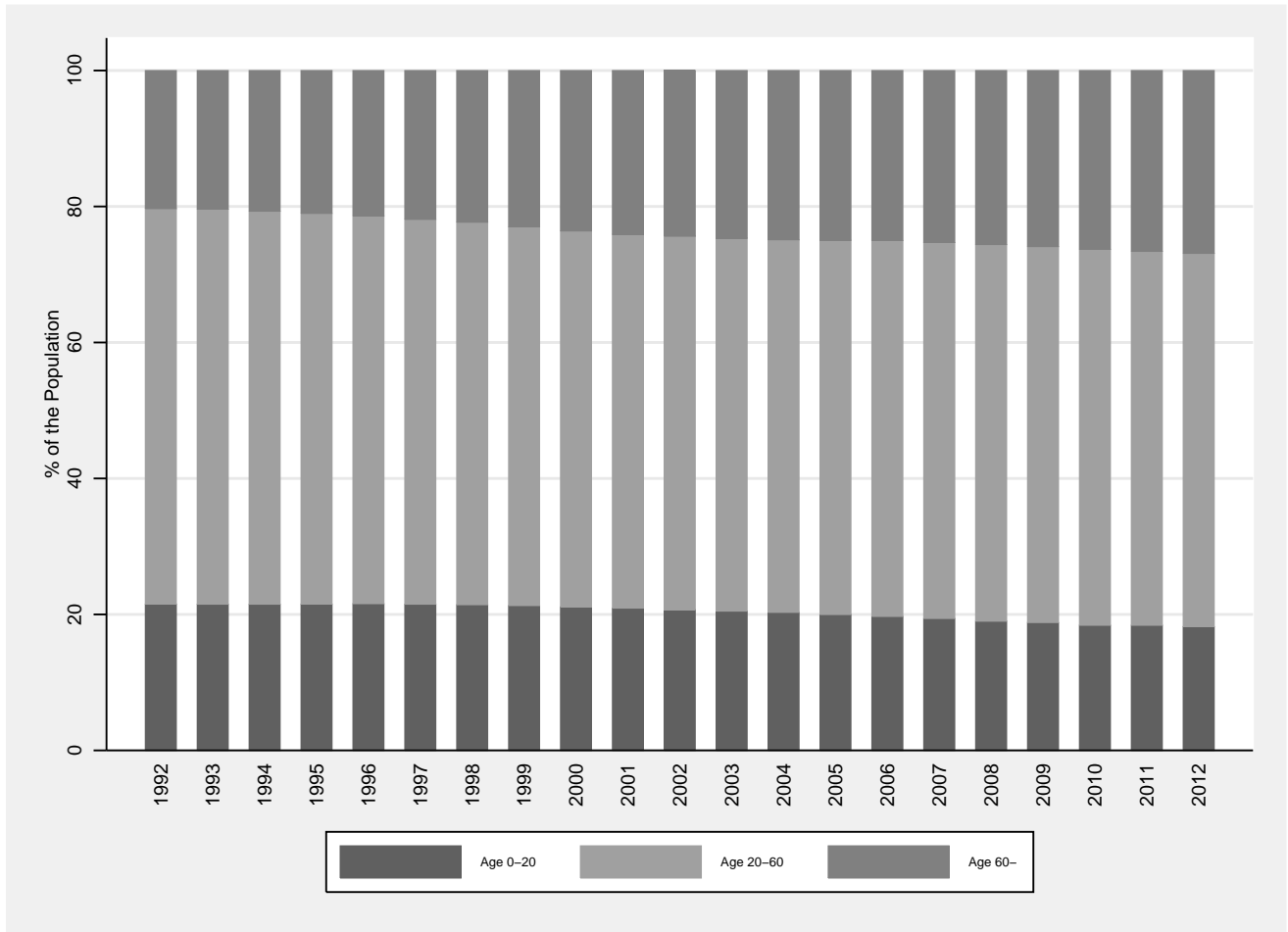


Notes: Own illustration based on data from the OECD. The figure shows the development of HCE in percent of GDP for five OECD countries.

of its development and, hence, finding means to counteract the steady increase of HCE in most of the OECD countries, is intensively discussed in the scientific literature.

Two factors have been identified to be main determinants of HCE: demographic change and technological progress. Although the channel through which age affects HCE is controversially discussed in the literature, a positive correlation between the age structure of a society and its HCE is well established. One strand of the literature considers age itself as the main driver in explaining HCE and long-term care expenditures respectively (e.g. Colombier and Weber, 2011; Karlsson and Klohn, 2014). Older individuals have higher demand for both health services and health care than younger individuals and, hence, cause higher HCE. Advocates of the so-called 'red-herring' hypothesis, however, argue that not age itself but the proximity to death is the underlying mechanism that is most relevant in explaining the age-HCE-relationship (e.g. Zweifel et al., 1999; Werblow et al., 2007; Shang and Goldman, 2008). Once the end-of-life HCE are accounted for, age seems to have no considerable effect in explaining HCE. However, the ongoing demographic shift will increase the relative share of older individuals and further increase pressure on public finance, independent of the exact mechanism. For Germany, this aging process of the population is depicted in Figure 1.2. Compared to 1992, both the share of the population aged 20 and younger and the share of those in working age (20-60) decrease by around 3 percentage points in 2011. This, in turn, leads to an increase of about 6 percentage points, or 31 percent,

Figure 1.2: Demographic Change in Germany



Notes: Own illustration based on data from the German Federal Statistical Office. The figure shows the development of the demographic structure in Germany from 1992 to 2012.

in the share of individuals aged 60 and older. The progressive demographic change is already assessed by several strategies, such as creating more incentives to increase fertility rates or fostering migration. However, these policies – if at all – will become effective only in the long run and will not affect HCE in the short and medium run.

Apart from age-related drivers, technological progress has been identified to be a major determinant in explaining the development of HCE (e.g. Newhouse, 1992; Okunade and Murthy, 2002). Product innovations in form of new drugs and medical treatments cause a considerable part of the increase in HCE due to higher prices. Newhouse (1992), for instance, attributes almost half of the increase in HCE to technological progress. In contrast to the demographic change, technological progress, which often increases quality of life for a large share of the population, in particular for those with chronic diseases, is a highly favored development. Therefore, reducing or even stopping technological progress by policy interventions is unlikely to be the right way to lower HCE.

Although age-related factors and technological progress have been found to be important determinants of HCE and its development, they are either hardly influenceable (demographic change) – at least in the short and medium run – or even not intended to be reduced/stopped by policymakers (technological progress). Therefore, finding more direct measures to assess and control HCE in the short and

medium run is an important issue for policymakers. Apart from rationing and prioritization, which constitute potential candidates for reducing HCE in the short and medium run, there exist two further possibilities that do not rely on direct shortenings of health care provisions: increasing efficiency of the existing health care system and reducing the prevalence of preventable risk factors in society.

Increasing efficiency of health care systems has been subject of several reforms in Europe and many other countries over the last decades (e.g. Oliver, 2005; Schut and Van de Ven, 2005; Wörz and Busse, 2005; Wagstaff and Moreno-Serra, 2009; Moreno-Serra and Wagstaff, 2010). Apart from different financing systems and various reimbursement schemes for providers, fostering competition on health care markets, in particular on the health insurance market, has received attention in Germany as well as many other countries. The German health insurance system is characterized by the coexistence of statutory (SHI) and private health insurance (PHI). While the SHI covers more than 80% of the population – most of them mandatory – and currently consists of around 130 sickness funds, the private system is accessible only for a selected group of the population, such as higher earners, civil servants and self-employed individuals, and comprises around 40 different insurance companies. Apart from minor differences in the benefit packages, a main difference between both systems concerns premium calculations.<sup>2</sup> While premiums under SHI are predominantly related to individuals' income, premiums under the PHI are solely determined by individuals' risk factors, such as age or their medical history. Due to the fact that certain subgroups of the population may choose between both systems, competition takes also place between both systems. This is usually discussed in terms of concerns about efficiency, as potential selection in favor of the PHI may lead to undesirable market outcomes, and fairness, as only certain groups of the population have the freedom of choice between both systems. Although these debates have lasted a long time already and are still ongoing, the empirical evidence on who prefers which type of insurance is rare and inconclusive. Therefore, chapter 2 of this thesis empirically assesses the role of incentives related to the regulatory framework and to what extent individual switching behavior between both systems can be attributed to these incentives.

The possibility to switch from SHI to PHI and, hence, competition between both systems is limited to a small group of the population. In contrast, the majority of the German population is insured under the SHI, which is why a large part of efforts made to increase competition in the German health insurance market refers to the SHI. Prior to 1996, most individuals insured under the SHI were assigned to sickness funds based on their occupation and could only indirectly influence their health insurance provider. Hence, competition between sickness funds was virtually non-existent. As one of the first attempts to foster competition in the SHI market and part of the Health Care Structure Act in 1992 (*Gesundheitsstrukturgesetz*), the right of freedom of choice of sickness fund was introduced in 1996. To account for the historical differences in the risk-structure between sickness funds, a risk-equalization scheme was introduced two years in advance. The second major step towards more competition among sickness funds in the SHI was enacted by a health care reform in 2007 (*GKV-Wettbewerbsstärkungsgesetz*). As one part of this reform, health insurance contribution rates, which were set independently by each sickness fund prior to 2009, were equalized across sickness funds. If a sickness fund's expenditures exceed its revenues, the insurance provider has to charge an additional premium from its members. To increase price transparency, this additional premium is expressed in

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<sup>2</sup>Another important difference between both systems concerns the remuneration system for physicians (Schmitz, 2013).

absolute monetary values and is independent of individual income.<sup>3</sup> However, only a small group of sickness funds were forced to charge such an additional premium. In addition to the change in premium calculation, the health care reform of 2007 has provided some new opportunities for sickness funds to differentiate from each other. Although most ( $\approx 95\%$ ) of the already very generous benefit package is determined at the federal level, sickness funds may offer voluntarily additional services, for instance, in the form of special health plans (optional tariffs), such as plans with deductibles. However, in order to render these reforms effective, it is necessary that individuals react to these moderate differences between sickness funds and switch their current sickness fund if they find a better option. Moreover, apart from the desired effect, a spillover effect of stimulating competition among health insurers may also create incentives for risk-selection which, in turn, would counteract any efficiency gains. Against this regulatory background, chapter 3 of this thesis analyzes individual switching behavior within the German SHI market. More specifically, we investigate how sickness funds enrollees value prices relative to supplemental benefits and service quality. In addition, we test whether various groups of the population react differently to these characteristics, which – if this is the case – might be carefully interpreted as a first indication for means of indirect risk selection of sickness funds in the SHI.

Besides increasing efficiency of the health care system, the second possible strategy in the fight against increasing HCE is reducing the prevalence of preventable risk factors that increase the probability of developing a disease or the likelihood of dying. Preventable risk factors can be subdivided into two broad categories: behavioral and environmental risk factors. The former category comprises risk factors that are influenceable – at least to a great extent – by individuals themselves, such as tobacco consumption, physical (in)activity or obesity. According to the World Health Organization (2009), the latter three factors range among the top five risk factors causing deaths in high-income countries with tobacco use as the leading cause. Reducing the prevalence of these preventable risk factors, in particular with respect to tobacco consumption, has gained increasing attention of health policymakers. Apart from rising tobacco taxation and certain advertisement bans, which, for example, were already introduced in Germany in the seventies, many of the policy interventions went effective over the last decade. This, especially, holds true for the introduction of several smoking bans, for instance in public buildings, schools or bars and restaurants, and various information campaigns, such as anti-smoking television campaigns or text warnings on cigarette packages. While the former mainly aims at reducing the exposure of non-smokers to second-hand smoke, the latter is intended to inform individuals about the harmful consequences of smoking and, hence, to prevent non-smokers from taking up smoking and motivate smokers to quit. Again, effectiveness of such interventions depends on whether individuals react in the desired way. If and to what extent individuals adjust their health behavior as a consequence of new health information is investigated in chapter 4 of this thesis. Specifically, I analyze whether the occurrence of a health problem, which represents a specific type of information, increases the likelihood of smoking cessation.

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<sup>3</sup>As compared to the former regulation, where premium differences were expressed in relative terms, this can also be interpreted as a change in price framing. However, a recent reform enacted in 2014 (*GKV-Finanzstruktur- und Qualitäts-Weiterentwicklungsgesetz*) will change the existing regulation so that additional premiums will be expressed in relative (income dependent) instead of absolute terms as of January 2015. This, in turn, will lead to essentially the same situation with respect to price differences between sickness funds as before 2009, where premium differences were expressed in relative terms.

The second category of preventable risk factors consists of those factors that relate to characteristics of an individual's living environment, such as air pollution, noise pollution or crime. In contrast to behavioral risk factors, environmental risk factors are not directly influenceable by individuals themselves. Some of these environmental characteristics and their potential spillover effects on individual health, most notably air and noise pollution, are already subject to an intense scientific as well as public debate (e.g. Janke, 2014; Bilger and Carrieri, 2013; Brink, 2011; Boes et al., 2013). The increased awareness of the effects of environmental characteristics is also reflected by several recent policy interventions that aim at reducing individuals' exposure to these risk factors, such as bans on night flights or the introduction of low-emission zones in larger cities that became effective in Germany over the last years. While these prominent factors often lead to measurable impact on individuals' physical health and, therefore, are in the focus of public interest, other potential threats that mainly affect individuals' mental well-being have gained less attention. Understanding the role of environmental risk factors with respect to mental well-being is also emphasized by increasing prevalence rates of mental health problems, which have become a major concern in many developed societies. In Germany, for example, the number of diagnoses related to mental and behavioral disorders have increased by around 33 percent from 2000 to 2012 (Federal Statistical Office Germany, 2014b). In the same period of time, deaths caused by mental health problems have even increased by about 260 percent (Federal Statistical Office Germany, 2014a). Against this background, chapter 5 considers potential spillover effects of local crime rates on mental well-being of inhabitants. Crime and its potential spillover effects on mental well-being are one example for environmental risk factors that are hardly considered, at least in the economic literature. Although these factors might have a small impact on the individual level, the fact that a large share of the population is exposed to numerous risk factors may lead to substantial aggregate effects on HCE.

The remainder of this thesis is structured as follows: in the next two subsections, I briefly discuss the data and methods used in the subsequent studies and provide a short summary of each of the following four chapters. Each of these chapters constitutes a self-containing empirical study in the field of health economics and addresses research questions related to either efficiency aspects in health insurance markets or the understanding of the prevalence of preventable risk factors. The former is addressed by chapters 2 and 3, which consider health insurance switching behavior between SHI and PHI and within the SHI respectively in the German context. The latter is covered by chapters 4 and 5, which investigate individual and environmental risk factors respectively. Concluding remarks are given in chapter 6.

## 1.2 Data and Methods

This thesis consists of four self-containing chapters, however, all of which have in common that they exploit individual-level panel data in order to address the research questions under consideration. Three out of the four studies (chapters 2, 3 and 5) make use of data taken from the German Socio-Economic Panel (SOEP). The SOEP is a nationally representative survey for Germany and provides detailed information on both the household and individual level. Since 1984, the SOEP collects annually comprehensive information about an individual's socioeconomic status, such as demographic, labor market or educational characteristics, but also about personal opinions and attitudes from all household members aged 17 and older. In addition, the SOEP covers detailed information about various topics related

to health, health behavior and health insurance membership, which makes it especially suitable for studies in empirical health economics. Currently, the SOEP consists of around 20,000 individuals from 10,000 households.

In chapter 4, however, the empirical analysis relies on individual-level data extracted from the Swiss Household Panel (SHP), which can be considered as the Swiss counterpart to the SOEP. Specifically, the SHP is a representative longitudinal survey that collects annual information of all household members aged 14 and older from over 5,000 households in Switzerland. The SHP survey has started in 1999 and comprises – similar to the SOEP – a large battery of questions related to individuals' socioeconomic status but also with respect to their health and health behavior. In particular, the SHP includes more detailed information about the occurrence of a sudden health problem as compared to the SOEP that only provides indirect information about health events, for example in the form of changes in self-reported health status. Although considerably smaller in its absolute sample size ( $\approx 7,000$  observations per wave) as compared to the SOEP ( $\approx 20,000$  observations per wave), the information about different sorts of health problems and their time of occurrence, makes the SHP especially attractive for the research question under scrutiny in chapter 4, i.e. if and how different types of health problems affect individuals' health behavior in terms of smoking cessation.

The micro-econometric techniques employed in the different chapters of this thesis are determined by the underlying research question and, strongly related, by the nature of the respective outcome variable of interest. To account for the fact that most of the outcome variables in the subsequent analyses are categorical, I use appropriate variants of standard probit and logit models. Specifically, chapter 2 applies a bivariate ordered probit model, chapter 3 uses a random parameters model (mixed logit) model and chapter 4 employs *Firth's* method – a modification of the standard logit regression. Although limited dependent variable models have the advantage that they explicitly take into account the categorical nature of the outcome variable, a disadvantage of these models is that they need additional functional form assumptions. In chapter 5, however, I opt for classical ordinary least squares (OLS) techniques, as the outcome variable under consideration has almost cardinal character.

A primary aim of most empirical analyses, at least in the economic literature, is to investigate causal relationships between the outcome and key explanatory variable(s) of interest. Moreover, giving an indication of the absolute magnitude of the effect under consideration and, hence, its economic relevance, is often an additional goal of empirical economic studies. In the context of rising HCE, distinguishing between simple correlations and causal relationships seems to be particularly important, as a better understanding of the underlying mechanisms is a necessary precondition to develop policy interventions that effectively counteract the increasing trend of overall HCE. Yet, establishing causal relationships or even quantifying them is empirically challenging – if possible at all – and usually holds only under a specific set of assumptions. In order to test or even relax at least some of these assumption and, hence, reduce concerns about endogeneity of the key explanatory variables, I pursue different strategies throughout this thesis. First, I exploit the nature of panel data to allow for unobservable time-invariant confounding variables that might bias the estimation results. In cases where this is not feasible due to model restrictions, in particular with respect to the discrete time hazard models estimated in chapters 2 and 4, I use instrumental variable (IV) techniques and conduct additional robustness checks respectively. Second, I also use objective and publicly available data on a more aggregated level in chapters 3 and 5. This data is linked to the self-reported individual-level data from

the SOEP in order to reduce endogeneity concerns. However, it is important to keep in mind that only some of the assumptions necessary to establish a causal relationship can be addressed. Therefore, causal statements and their quantification are only of suggestive, not conclusive character in this thesis.

## 1.3 Summary of the Four Studies

### **Chapter 2: Who Opt Out of the Statutory Health Insurance? A Discrete Time Hazard Model for Germany**

The German health insurance system is characterized by the coexistence of SHI and PHI. The fact that the majority of the German population is insured under the SHI – most of them mandatory – while certain subgroups of the population, such as civil servants, the self-employed and high earners, may opt out for substitutive PHI has been the subject of intense discussions in terms of both efficiency and fairness. Potential positive selection into the PHI, mainly due to risk-adjusted health premiums under the PHI, may lead to undesirable market outcomes in the German health care market. In addition, privately insured are often considered as privileged because of different and possibly better medical treatments. Although the regulatory framework and related incentives clearly suggest who will prefer which type of insurance, the empirical evidence is still inconclusive. In chapter 2 we investigate determinants that led individuals to switch the type of insurance using data from the SOEP for the years of 1997-2010. Besides socioeconomic characteristics and health risks, which are suspected to be the main drivers in this decision, we also analyze the role of previously unconsidered personality traits, such as risk aversion or altruistic attitudes, that could affect the decision to opt out of the SHI. Applying a hazard model in discrete time and accounting for potential endogeneity of self-reported health through an IV approach, the estimation results yield robust evidence on the choice of health insurance type that is consistent with pragmatic decision making, with both incentives set by regulation and personality traits as relevant determinants. For instance, the SHI is preferred by individuals who benefit from free insurance coverage of dependents or those who would have to pay high risk-adjusted premiums under the PHI, i.e. bad health risks. This advantageous selection in favor of the PHI may further increase pressure on the SHI which is already severely affected by demographic change. In addition, we also find convincing empirical evidence for the notion that risk-loving individuals have a higher probability of buying PHI, however, we observe no significant effect of the measure of altruism. Overall the results suggest that the choice between both systems seems to be a less emotional issue and, hence, policy debates should focus more on how to design a framework that foster more competition between both systems.

### **Chapter 3: How Health Plan Enrollees Value Prices Relative to Supplemental Benefits and Service Quality**

One promising road to make the health insurance market more efficient is to increase consumers literacy by providing them with relevant information along with a set of potential choices. Sickness fund choice in the German SHI essentially depends on price, additional benefits and service quality of the insurer. While a substantial body of empirical literature investigates the effect of price on sickness



fund choice, only a few consider the role of benefits and quality. The study presented in chapter 3 is one of the rare studies that empirically assesses the role of sickness fund prices, service quality and optional benefits in the decision to choose sickness funds. We investigate the role of prices, non-essential benefits and service quality in the German context and link individual-level data from the SOEP to publicly available sickness fund characteristics from 2007 to 2010. We estimate random parameters models which account for both heterogeneity in individual preference and time-invariant unobserved sickness fund characteristics and incorporate around 1,700 health plan choices with more than 50 selectable sickness funds in individuals' choice set. The empirical results suggest that prices play the dominant role and that the provision of non-essential benefits as well as service quality seem to play a negligible role in sickness fund choice in Germany. In quantitative terms the results suggest that a one standard deviation increase in any considered benefit and service quality measure is absorbed by a one-eighth standard deviation increase in premiums. Even if benefits and service quality affect sickness fund choices, individuals are willing to trade them against premiums at a rather small rate. Additional heterogeneity analyses indicate that differences in preferences with respect to the characteristics under consideration are rather small across various groups, suggesting that non-essential benefits and service quality seem to constitute no means of indirect risk selection of sickness funds. Altogether the results indicate that increasing sickness funds' freedom to diversify more in non-price attributes might constitute an appropriate tool to strengthen competition in the German SHI market.

### **Chapter 4: Does New Health Information Affect Health Behavior? The Effect of Health Events on Smoking Cessation**

Tobacco consumption is the second leading risk factor causing deaths worldwide (World Health Organization, 2009), translating into more than 5 million deaths each year. To reduce smoking prevalence, it is necessary to investigate which strategies might be effective tools in the fight against tobacco consumption. In chapter 4, I empirically assesses the role of new health information in the decision to quit smoking. Specifically, I test whether health information induce behavioral change, i.e. smoking cessation, at all and whether different types of information affect the decision to stop smoking differently. Using individual level data from the SHP, health information is proxied by three different types of health events: physical health problems, mental disorders, and accidents. Exploiting retrospectively reported information on smoking behavior, getting away from tobacco consumption is modeled in the fashion of a discrete time hazard model with smoking cessation as the absorbing state. In order to account for the presence of an almost quasi-separation problem with respect to one of the key explanatory variables of interest, I estimate a modified version of the standard likelihood function obtained from a logit specification. The empirical results yield robust evidence that smokers adjust their health behavior as a consequence of a health event. Differentiating between the type of health event reveals that the positive overall effect is mainly driven by physical health events. On average, the occurrence of a physical health event increases the probability of instantaneous smoking cessation by 3.5 percentage points. Against the average predicted probability to quit, which amounts to 4.2 percent, this is a substantial impact. The results for mental health problems are less conclusive. While the estimated coefficient points towards a remarkable negative effect on the likelihood of smoking cessation, it is statistically not significant. Accidents, in turn, have virtually no impact on the decision to quit smoking. These results remain qualitatively and quantitatively robust to a battery of additional robustness

checks. Overall, the empirical results suggest that individuals react to new health information in the form of health problems, in particular to those that are closely related to their own health behavior. Hence, facing individuals with the harmful consequences of their own health behavior, for example through text warnings and shocking pictures on cigarette packages, seems to be a promising tool to increase individuals' risk perception and, hence, to reduce smoking prevalence and thereby HCE.

### **Chapter 5: Does the Burglar Also Disturb the Neighbor? Crime Spillovers on Individual Well-being**

Criminal activities account for large individual and societal costs all around the world. While costs related to direct victimization, i.e. tangible costs (e.g. property loss, medical bills, foregone income) and intangible costs (e.g. behavioral changes, emotional responses), are in themselves already substantial, they do not account for indirect costs in the form of psychological responses that criminal activity induce through a fear of victimization among both victims and non-victims. Since these indirect costs of crime are not restricted to a certain group of the society (e.g. victims) but rather affect whole communities, they may potentially constitute a much greater cost factor than costs attributable to direct victimization. In chapter 5 we contribute to the growing literature on quantifying the indirect costs of crime by investigating how variation in local crime rates affects the mental health of residents in a previously largely unexplored country: Germany. Linking official crime statistics for the whole of Germany to individual-level mental health information from the German Socio-Economic Panel and exploiting variation in local crime rates over time, we estimate that a one standard deviation increase in local crime rates significantly decreases individual mental well-being among residents by, on average, one percent (0.442 MCS points) for violent crimes. This estimate corresponds to approximately half of the impact of becoming unemployed or to an additional societal cost of €16,800 per violent crime. Smaller effects are found for property and total crime rates. The estimation results are insensitive to migration and not isolated to large or urban areas, but are rather driven by less densely populated regions. Finally, we find, in contrast to previous literature on vulnerability to crime, that men, more educated and individuals without children react more to variation in violent crimes in their neighborhoods. One potential explanation could be that those who are more fearful of crime have developed better coping strategies and, hence, react less to changes in crime. Altogether, our results confirm earlier findings that local crime affects mental well-being of residents but also contribute with empirical evidence that these effects varies along a number of dimensions, such as the societal, geographical and demographical context. Such insights into the complexity of the relationship between crime, fear of crime and its spillover effects on individuals' mental health suggest that reducing psychological impacts of crime needs more customized strategies depending on the context at hand.

## Chapter 2

# Who Opts Out of the Statutory Health Insurance? A Discrete Time Hazard Model for Germany

### 2.1 Introduction

The German health insurance system has been the subject of intense public as well as scientific debates (e.g. Wörz and Busse, 2005; Jacobs et al., 2006; Fehr and Jess, 2006; Schubert and Schnabel, 2009). A crucial issue in these debates – apart from financing issues – concerns a decisive feature of the German system: the coexistence of social health insurance (SHI) and private health insurance (PHI). While for the majority of the German population, roughly 80 percent, insurance under the SHI is mandatory, certain groups of the population may opt out and purchase substitutive PHI (these groups may also stay in the SHI as voluntary members). This exemption from the SHI applies to civil servants, self-employed people, and high-earning employees. Of the latter, however, less than one quarter actually choose private insurance coverage (Thomson et al., 2002).

Who selects PHI and who prefers to stay under the SHI is usually discussed primarily in terms of concerns about efficiency and fairness. Potential adverse selection at the expense of the SHI may lead to undesirable outcomes in the German health insurance market (Greß, 2007). Moreover, holders of private health insurance might receive different and possibly better medical treatment than publicly insured individuals, as physician compensation is higher for private patients (Jürges, 2009). Lungen et al. (2008), for instance, observe shorter waiting times for privately insured persons and Gruber and Kiesel (2010) find a higher rate of specialist utilizations among privately insured men. Hulleger and Klein (2010) even observe a positive overall effect of being privately insured on self-reported health.

Based on the regulatory framework and different features of both systems, which are covered in more detail in section 2.2, the existing literature clearly suggests who should prefer which type of insurance

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This study is joint work with Harald Tauchmann. See Bunnings and Tauchmann (2014) for a published version of this chapter.

(e.g. Thomson and Mossialos, 2006; Wasem et al., 2004). The empirical literature on the actual choice between the SHI and PHI, however, yields ambiguous results. The present paper provides further empirical evidence on how incentives set by the regulatory framework affect the inclination to switch from the SHI to PHI. Moreover, the literature provides some indication that other, previously unconsidered factors, such as attitude towards risk, may also have an effect on the choice of insurance type. We include several personality traits in the empirical model to analyze their potential effects and to test whether they lead to different behavior than suggested by pure financial incentives.

Using individual level data from the German Socio-Economic Panel of 1997-2010, switching from the SHI to PHI is modeled in the fashion of a discrete time hazard model. Additionally, we adopt an instrumental variable approach that accounts for potential endogeneity of one of our key variables. The estimation results suggest that switching behavior can be explained to a great extent by the incentives set by the regulatory framework. Yet, we also observe a considerable impact of personality traits on the inclination to opt out of the SHI. Overall, the results yield robust evidence that individuals act on a pragmatic basis.

The rest of this paper is organized as follows. Section 2.2 discusses institutional features of the German health insurance system that are relevant for the investigation of switching behavior from the SHI to PHI. Section 2.3 describes the data set used in the empirical part, and section 2.4 outlines the econometric models used for the estimation. Section 2.5 provides the estimation results, and section 2.6 concludes.

## 2.2 Institutional Background and Related Incentives

In Germany, the SHI is a pay-as-you-go system based on solidarity as the underlying principle where contributions are redistributed across several dimensions, e.g. age, health status, income or family composition (Wasem et al., 2004). Insurance under the SHI is mandatory for all employees who earn less than the relevant income threshold (*Versicherungspflichtgrenze*: 53,550 EUR in 2014).<sup>1</sup> Employees with annual income above this ceiling can either remain in the SHI as a voluntary member or purchase substitutive PHI instead. Apart from high-income individuals, civil servants and self-employed people are also allowed to choose between the two systems regardless of their earnings. Out of total of 62.2 million insurance holders<sup>2</sup> in 2011, 80% were mandatory members under the SHI, 5% were voluntarily insured under the SHI, while 15% were covered by PHI (Federal Ministry of Health, 2013).

Once an individual has chosen private insurance coverage, switching back to the SHI is restricted to cases where an individual becomes subject to compulsory insurance again.<sup>3</sup> In order to prevent opportunistic behavior, individuals aged 55 and older are generally not allowed to switch back to the SHI.<sup>4</sup> Hence, opting out of the social system is often a lifetime decision. Therefore, this analysis only

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<sup>1</sup>The income threshold is adjusted on a yearly basis. From 2000 to 2014, the income threshold was raised by roughly 2% on average each year. Employees are eligible for PHI in  $t$  if their annual income, including all extra payments, exceeded the threshold in  $t - 1$ .

<sup>2</sup>This number does not include roughly 18 million family members, subject to free family insurance under the SHI.

<sup>3</sup>This applies to employees if annual earnings fall below the income threshold for at least one year or if they become unemployed. Civil servants and self-employed people are eligible to switch back to the SHI only if they take up a blue- or white-collar occupation and, at the same time, earn less than the relevant income threshold.

<sup>4</sup>Otherwise, young healthy individuals could benefit from lower, risk-adjusted PHI premiums and then switch back to the SHI at an older age when PHI premiums become more unattractive.

considers switchers from SHI to PHI, as switching back to the SHI is typically attributable to exogenous events rather than to individual choice.

The choice between SHI and PHI is closely related to several institutional differences between the two systems. Perhaps the most essential difference concerns premium calculations. In the SHI, premiums are based solely on income. That is, independent of individual risk factors, employees pay a certain percentage (8.2% in 2014) of their annual gross earnings up to the current social security contribution ceiling (*Beitragsbemessungsgrenze*: 48.600 EUR in 2014). The employer's contribution amounts to 7.3% (2014) of employee's gross earnings up to the current social security contribution ceiling. Basically, this also applies to the employer's contribution for PHI insurants.<sup>5</sup> In contrast, premiums in the PHI are capital-funded and determined solely by risk factors such as age, gender, and health risks. Moreover, private health insurers are legally obliged to build up old age provisions to prevent premiums from increasing too strongly with age.<sup>6</sup> While in the SHI the scope of coverage and the premium amounts are almost completely predetermined by legislation, the PHI offers more flexibility in contract design, which gives rise to contracts with fairly low premiums.<sup>7</sup> Financial incentives to choose PHI are even stronger for civil servants, as they are entitled by law to a subsidy from their public employer for PHI (*Beihilfe*) of 50% to 70%, and even up to 80% for dependent children, depending on family status and the employment level (federal / state). Self-employed people bear the full cost of insurance coverage themselves, regardless of the type. Finally, SHI may be especially attractive for families, since a member's non-working spouse, and under certain conditions children under 25, are covered at no additional cost. Free insurance coverage of dependents does not apply to PHI, where a separate premium is charged for each insurant.

Even though the existing literature clearly suggests – against the background of these regulatory conditions – who will prefer which type of insurance, the empirical literature on the choice between SHI and PHI yields ambiguous results. Most studies provide descriptive analyses on differences in socioeconomic status, health, and health behavior between those who are insured under the SHI and those who are covered by PHI (e.g. Greß, 2007). Cross-sectional descriptive analyses allow only partial explanations for the choice of insurance type, in particular since the decision is driven by an individual's socioeconomic characteristics at the time of the decision, not by characteristics held at the time of the survey. Switching behavior based on individual-level data has rarely ever been analyzed; Grunow and Nuscheler (2014) are a notable exception. They provide empirical evidence for risk selection in favor of private insurers, as individuals in poorer health are more likely to switch back to the SHI. Thus, the financial burden of bad health risks is passed on to the solidary community, while private insurers benefit by retaining the accrued old age provisions. Risk selection would also take place if individuals of better health were more inclined to switch from the SHI to the PHI. Though statistically insignificant, the estimated coefficient suggests that there is some effect of this sort. Considering the other incentives mentioned above, the results of Grunow and Nuscheler (2014) partially conflict with expectations derived from the literature. For instance, they observe no significant effect of either family composition or occupation on the probability of switching in their model, an instrumental variable es-

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<sup>5</sup>The contribution paid by the employer is 7.3% up to the current social security contribution ceiling but not more than 50% of the actual PHI premium.

<sup>6</sup>Though private insurers are not allowed to readjust an individual's premium due to changes in his risk-profile, there are other factors that cause PHI premiums to rise, for instance medical progress and increasing life expectancy.

<sup>7</sup>Insurants may choose different levels of deductibles and coverage by in- or excluding certain services.

timator with individual fixed effects. This might be attributable to insufficient within-group variation in these variables.

Furthermore, Thomson and Mossialos (2006) provide some indication that other, previously unconsidered factors could have an effect on the decision to opt out of the SHI. Given the nearly irreversible character of switching to PHI, they emphasize the role of attitude towards risk, as switching to PHI is associated with risk in terms of uncertainty about future earnings, as PHI contributions are not related to income, and because of uncertainty about future health care needs and family size. Moreover, it is also conceivable that altruistic behavior in itself provides a motivation to stay in the SHI. Individuals with an altruistic attitude might prefer the SHI if they were aware of their contribution to the system of redistribution. Therefore, this paper also analyzes whether personality matters for the decision to switch to PHI, and whether controlling for personal traits affects the impact of the financial incentives set by the regulatory framework.

## 2.3 Data

This analysis is based on data from the German Socio-Economic Panel (SOEP).<sup>8</sup> The SOEP is a German representative longitudinal survey that provides extensive information on both the household and the individual level. On an annual basis, all household members aged 17 and older are interviewed on a wide range of socioeconomic characteristics, health and health insurance related topics, but also on their personal attitudes, opinions, and values. SOEP has run since 1984, and – following various refreshments and enhancements – currently comprises more than 20,000 individuals from more than 10,000 households per year (Wagner et al., 2007).

The estimation sample is restricted to all person-year observations for which an individual has the opportunity to opt out of the SHI. This applies to civil servants and self-employed people independent of their annual income. In addition, employees with income exceeding the relevant threshold in the previous year(s) may also opt for PHI. To classify whether an individual is eligible to leave the SHI, we primarily exploit information on occupation and income, and include individuals who reported to be either a civil servant or being self-employed or being employed with annual income above the threshold. Our basic estimation sample, however, also comprises employees who reported to be a voluntary member under the SHI but for which reported income did not exceed the relevant threshold. A binary indicator (*extended*) to mark those individuals enters the right-hand-side of all regression models.<sup>9</sup> We only consider individuals aged 20 to 60, as this is the group for which choosing between PHI and SHI is a relevant question. Younger individuals are usually covered by family insurance, while switching becomes quite unattractive for older people due to disproportionately high premiums caused by risk adjustment and a lack of old age provisions. The estimation sample covers the period 1997 to 2010 and consists of 20,244 person-year observations stemming from 5,980 individuals who

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<sup>8</sup>In order to extract data, we use the add-on package PanelWhiz v4.0 (Sep 2010) for Stata, written by John P. Haisken-DeNew (john@panelwhiz.eu). Haisken-DeNew and Hahn (2010) describe PanelWhiz in more detail. Any data or computational errors in this paper are our own.

<sup>9</sup>SOEP participants are asked whether they are voluntarily or compulsorily insured under the SHI. We also rely on the reported insurance status as this is probably less sensitive information than individual income.

Table 2.1: Sample Characteristics

| Panel A: Sample Selection              |       |   |       |             |       |
|--|-------|---|-------|-------------|-------|
| Civil servants:                        | 689   | Self-employed people:                               | 5,236 |             |       |
| Employees (income $\geq$ threshold):   | 9,178 | Employees (income < threshold) ( <i>extended</i> ): | 5,141 |             |       |
| Panel B: Observations by Calendar Time |       |   |       |             |       |
| 1997:                                  | 1,000 | 2000:   | 1,787 | 2003:       | 2,067 |
| 1998:                                  | 1,107 | 2001:   | 1,895 | 2004:       | 1,721 |
| 1999:                                  | 1,212 | 2002:   | 2,123 | 2005:       | 1,636 |
|  |       |   |       | 2006:       | 1,646 |
|  |       |   |       | 2007:       | 1,395 |
|  |       |   |       | 2008:       | 1,350 |
|  |       |   |       | 2009:       | 1,305 |
| Panel C: Observations by Time at Risk  |       |   |       |             |       |
| 1:                                     | 4,462 | 3:  | 2,320 | 5:          | 1,510 |
| 2:                                     | 3,029 | 4:  | 1,825 | 6:          | 1,284 |
|  |       |   |       | 7:          | 1,097 |
|  |       |   |       | 8:          | 889   |
|  |       |   |       | 9:          | 679   |
|  |       |   |       | $\geq 10$ : | 3,149 |
| Panel D: Observations per Individual   |       |   |       |             |       |
| # 1:                                   | 5,980 | # 4:  | 2,007 | # 7:        | 995   |
| # 2:                                   | 3,649 | # 5:  | 1,547 | # 8:        | 755   |
| # 3:                                   | 2,647 | # 6:  | 1,223 | # 9:        | 532   |
|  |       |   |       | # 10:       | 384   |
|  |       |   |       | # 11:       | 249   |
|  |       |   |       | # 12:       | 178   |
|  |       |   |       | # 13:       | 98    |

Notes: Own calculations based on the SOEP. The frequencies shown relate to the full sample of 5,980 individuals and 20,244 person-year observations.

were eligible for switching to PHI.<sup>10</sup> Of those, 13% (785) actually did switch in our sample during the period under consideration. Table 2.1 provides further information on the sample selection and how observations are distributed over time and individuals.

The dependent variable is a binary indicator based on the reported type of insurance. It equals one in the period before an individual first reported to be privately insured.<sup>11</sup> In all previous observations the dependent variable is zero. Some individuals switch several times between both systems. This is mostly explained by misreporting of insurance status, as switching to PHI is almost irreversible and only allowed if strict conditions are met. In order to mitigate this kind of error, we let an individual enter the sample only until she has switched to PHI for the first time and ignore later observations of this individual.

To investigate determinants that influence the inclination to switch, we include a rich set of explanatory variables which can be categorized in four groups. The first group provides the basis for analyzing switching behavior and comprises socioeconomic characteristics, as they are strongly related to incentives set by the regulatory framework. Aside from gender, age at inception date is an important determinant of premium amounts under the PHI, as older individuals represent higher health risks and have less time to build up the obligatory old age provisions.<sup>12</sup> Age enters the model in terms of four categories for individuals aged 20-29 years, 30-39 years, 40-49 years, and 50-60 years. We account for the effect of free insurance coverage of dependents under the SHI by including a separate dummy for children younger than 25 and for a non-working spouse. Since occupation, in particular being a civil servant, may also affect the insurance choice, indicator variables for civil servants, self-employed indi-

<sup>10</sup>Due to a change in questioning, the SOEP contains no information on insurance status in 1996. From the 2010 wave only the type of insurance is used to construct the dependent variable for 2009.

<sup>11</sup>This ensures that all explanatory variables were determined before an individual switched from SHI to PHI.

<sup>12</sup>Women are charged higher premiums than men under the PHI as they represent a higher insurance risk due to their higher life expectancy. In March 2011, the European Court of Justice forced private insurers to offer gender-neutral premiums as of December 21, 2012. However, this ruling does not affect our sample, which covers the period 1997-2010.

viduals, white-collar, and blue-collar workers also enter the empirical model. We account for income by including current annual gross earnings in thousands of EUR and its second polynomial to capture potential non-linearities. Years of education, a dummy for German citizenship, and an indicator variable for West German residence complete the number of socioeconomic controls.

The second group of explanatory variables is related to health. Health, in particular health risks, might be a key determinant in analyzing switching from the SHI to PHI, as they directly affect premium amounts under the PHI. As an overall measure of health status, we use self-assessed health (SAH), which is reported on a scale of one (*very good*) to five (*bad*). Though SAH is a subjective measure, it has been shown to be a good predictor of both morbidity and mortality (Idler and Benyamini, 1997). Nevertheless, we also use two more objective health-related variables from the SOEP: the number of hospitalizations during the last year and whether an individual is legally classified as handicapped. These variables do not directly enter the basic model as explanatory variables, but are used to instrument the potentially endogenous variable SAH.

The third group comprises personality traits, which can be assumed to be time-invariant. As pointed out by Thomson and Mossialos (2006), switching to PHI is associated with uncertainty, which may prevent risk-averse individuals from taking this step. Moreover, considering that solidarity is the underlying principle of the SHI, one might also hypothesize that highly altruistic individuals are less likely to opt out of the SHI. In order to account for heterogeneity in personality, we use the *Big Five Inventory* (BFI-S), which was included in the SOEP in 2005 and 2009. The BFI-S is a 15-item questionnaire based on the *NEO Personality Inventory Revised* (McGrae and John, 1992a), which is used to assess five core dimensions of personality: extraversion, agreeableness, neuroticism, openness, and conscientiousness. Extraverts tend to seek excitement and have a higher tolerance of risk. Agreeable people are characterized by altruistic and cooperative behavior. Neuroticism captures differences in emotional stability such as how people handle negative emotions or unfamiliar situations. Openness reflects the appreciation for arts, cultural events, and curious ideas. Conscientiousness captures the tendency towards efficient and self-disciplined behavior.<sup>13</sup> We primarily use the information from the 2009 survey, as respondents might at this point be more familiar with these questions than in 2005 when the BFI-S was introduced. The information from 2005 is used for robustness checks. Following Dehne and Schupp (2007), we perform an exploratory factor analysis on the 15-item questionnaire to construct measures for each of the five dimensions.<sup>14</sup> We also use an alternative, probably more direct measure of risk-lovingness based on self-reported attitude towards risk. Self-reported willingness to take risks ranges from 0 (*risk averse*) to 10 (*fully prepared to take risks*). The raw information is collapsed into a binary variable indicating risk-lovingness, which is one if the average of self-reported willingness to take risks is greater than or equal to six.<sup>15</sup>

The fourth group of variables contains further controls. The probability of switching may depend on the duration of being at risk to switch. One might hypothesize that individuals who are willing

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<sup>13</sup>For more information on the Five Factor Model, see McGrae and Costa (1987) and McGrae and John (1992b).

<sup>14</sup>First, the 15 items are z-transformed so that each variable has a zero mean and unit variance. Based on these standardized items, we conduct an exploratory factor analysis. The resulting matrix of factor loadings is utilized to obtain the factor scores, which are linear combinations of the standardized items and the corresponding factor loadings. The calculated factor scores were standardized to have a mean of 50 and a standard deviation of 10. In contrast to Dehne and Schupp (2007), we use unweighted data in order to allow for bootstrap procedure that encompasses both stages of the estimation procedure; see section 2.4.

<sup>15</sup>Self-reported willingness to take risks is not included in each wave of SOEP.



Table 2.2: Individual Characteristics

| Variable                       | Mean  | Std. Dev. | Min.  | Max.  | Obs.   |
|--------------------------------|-------|-----------|-------|-------|--------|
| SAH                            |       |           |       |       |        |
| Very good                      | 0.11  | 0.31      | 0     | 1     | 20,244 |
| Good                           | 0.49  | 0.50      | 0     | 1     | 20,244 |
| Satisfactory                   | 0.30  | 0.46      | 0     | 1     | 20,244 |
| Poor                           | 0.09  | 0.28      | 0     | 1     | 20,244 |
| Bad                            | 0.01  | 0.10      | 0     | 1     | 20,244 |
| Socioeconomics characteristics |       |           |       |       |        |
| Age 20-29                      | 0.08  | 0.27      | 0     | 1     | 20,244 |
| Age 30-39                      | 0.29  | 0.45      | 0     | 1     | 20,244 |
| Age 40-49                      | 0.36  | 0.48      | 0     | 1     | 20,244 |
| Age 50-60                      | 0.27  | 0.44      | 0     | 1     | 20,244 |
| Female                         | 0.31  | 0.46      | 0     | 1     | 20,244 |
| Non-working spouse             | 0.12  | 0.33      | 0     | 1     | 20,244 |
| Children < 25                  | 0.61  | 0.49      | 0     | 1     | 20,244 |
| Income                         | 45.44 | 32.32     | 0     | 1200  | 20,244 |
| Education                      | 13.55 | 2.88      | 7     | 18    | 20,244 |
| Civil servant                  | 0.03  | 0.18      | 0     | 1     | 20,244 |
| Self-employed                  | 0.26  | 0.44      | 0     | 1     | 20,244 |
| White-collar                   | 0.57  | 0.50      | 0     | 1     | 20,244 |
| Blue-collar                    | 0.14  | 0.34      | 0     | 1     | 20,244 |
| Residence west                 | 0.80  | 0.40      | 0     | 1     | 20,244 |
| German                         | 0.95  | 0.21      | 0     | 1     | 20,244 |
| Personality traits             |       |           |       |       |        |
| Neuroticism                    | 48.32 | 9.56      | 24.48 | 78.58 | 14,945 |
| Openness                       | 51.19 | 9.13      | 15.99 | 89.31 | 14,945 |
| Extraversion                   | 49.40 | 10.20     | 14.68 | 75.62 | 14,945 |
| Agreeableness                  | 47.72 | 10.22     | 6.53  | 73.28 | 14,945 |
| Conscientiousness              | 50.82 | 9.17      | 6.37  | 71.60 | 14,945 |
| Risk-loving                    | 0.38  | 0.49      | 0     | 1     | 19,115 |
| Instruments                    |       |           |       |       |        |
| # Hospitalizations             | 0.15  | 1.12      | 0     | 60    | 20,152 |
| Disability                     | 0.05  | 0.22      | 0     | 1     | 20,152 |
| Further controls               |       |           |       |       |        |
| Awareness                      | 0.46  | 0.50      | 0     | 1     | 20,244 |
| Extended                       | 0.25  | 0.44      | 0     | 1     | 20,244 |
| Left-censored                  | 0.35  | 0.48      | 0     | 1     | 20,244 |

Notes: Own calculations based on the SOEP. The descriptives shown are based on the maximum number of observations used in the corresponding empirical analysis.

to opt out of the SHI will do so as soon as they get the opportunity. To account for how long an individual has already had the chance of leaving the SHI – his *time at risk* – a set of binary indicators is included. For those individuals who were already at risk when they entered SOEP, the decision whether or not to stay in the SHI could have been made already. Hence, another binary indicator is included to control for this kind of left-censoring. Furthermore, it is conceivable that individuals may not opt out of the SHI simply because they are not aware of the possibility of leaving the public system. We cannot directly observe whether an individual is aware of her opportunity to opt out. However, we construct a binary variable for awareness which is based on reported insurance status, i.e. voluntary or compulsory member under the SHI. An individual is assumed to be aware of her options if she states she is a voluntary member and simultaneously reports being either a civil servant, or self-employed, or having annual earnings above the relevant threshold. Finally, the sample period covers two policy changes that further restrict the opportunities to choose PHI for employees: In 2003,

the relevant income threshold was increased substantially by 13%, and since 2007 income has had to exceed the relevant thresholds in the three preceding years, rather than only in the previous year. To capture effects of these exogenous shocks, a set of yearly dummies also enters the econometric model. Descriptive statistics of individual characteristics used in our analysis are shown in Table 2.2.

## 2.4 Empirical Strategy

The empirical analysis considers switchers from SHI to PHI. Switching back to SHI is typically attributable to exogenous events rather than to individual choice, which is why the model can be interpreted as a hazard model in discrete time with PHI as the absorbing state. Each individual either *survives*, i.e. stays under the SHI, *fails*, i.e. switches to PHI, or leaves the sample because she is no longer allowed to choose between the systems, i.e. becomes a compulsory member under the SHI. The unobservable inclination to switch from statutory to private health insurance  $switch_{it}^*$  is specified by the following equation:

$$switch_{it}^* = SAH_{it}^* \gamma + X_{it} \beta + \varepsilon_{it} \quad (2.1)$$

Individuals and periods are indicated by the subscripts  $i$  and  $t$ , respectively.  $SAH_{it}^*$  contains the set of dummy variables for self-reported health status.  $X_{it}$  comprises socioeconomic characteristics, personality traits, and supplementary controls. Finally  $\varepsilon_{it}$  denotes a random error term, which is assumed to be normally distributed, allowing for the estimation of coefficients  $\gamma$  and  $\beta$  by a simple probit regression. Hence, rather than the unobserved variable  $switch_{it}^*$ , its binary counterpart  $switch_{it}$  serves as dependent variable of the regression model. As switching to the PHI is regarded as irreversible, the dependent variable is either zero in all periods (non-switcher) or exhibits a sequence of zeros that is completed by a single one (switcher).

To account for correlations between observations of the same individual, we use clustered standard errors that are robust to arbitrary intra-cluster correlation. As discussed in section 2.3, the five personality measures are generated by using an exploratory factor analysis and, for this reason, are generated regressors in the sense of Murphy and Topel (1985). Standard errors hence need to be adjusted. This is done by a bootstrap procedure that encompasses both the generation of the variables through factor analysis and probit estimation.

Though SAH is frequently used as proxy for overall health status, there are also indications in the literature that SAH may be correlated with other factors such as income and personal preferences (Doiron et al., 2008). By using a wide range of socioeconomic controls as well as personal traits, we already eliminate much of the potential effects of confounding variables that operate through SAH. Nevertheless, SAH may still suffer from endogeneity due to correlations with unobservables. For instance, Doiron et al. (2008) argue that individuals with the same objective health status may report different SAHs, as perceived health may depend on different comparison groups. These peer groups could also affect the choice of insurance type, which in turn would result in an endogeneity problem and in inconsistent estimates. To tackle potential endogeneity of SAH and to assess sensitivity of the results drawn from probit regression, we also adopt an instrumental variable approach and augment Equation 2.1 by the following equation:

$$SAH_{it}^* = Z_{it}\alpha + X_{it}\delta + \vartheta_{it} \quad (2.2)$$

Note that  $SAH_{it}^*$  is now considered as underlying continuous health measure, that is just reported in terms of the familiar 5-point categorical measure that directly enters Equation 2.1.  $X_{it}$  is the vector of covariates that also enters Equation 2.1 and  $\vartheta_{it}$  denotes a random error term.  $Z_{it}$  is a vector of instruments containing objective measures of health: the number of hospitalizations in the previous year and a dummy variable for being legally classified as handicapped. The intuition behind using hospitalizations and disability as instruments is that individuals may rate their health according to their recent health care utilization. With respect to exogeneity, we argue that hospitalization usually requires an objective medical assessment, and thus is hard to influence by a person herself. The same holds for disability status, which is typically not influenced by individuals but rather through exogenous shocks. To estimate both equations simultaneously, we assume a bivariate normal distribution with correlation  $\rho$  for the error terms  $\varepsilon_{it}$  and  $\vartheta_{it}$  and estimate a bivariate ordered probit model (Sajaia, 2008).<sup>16</sup> Endogeneity of SAH can be tested by conducting a Wald Test on the estimated error correlation. Any significant estimates of  $\rho$  distinct from zero would point towards endogeneity of SAH. Again, we use clustered standard errors and apply bootstrap resampling methods.

## 2.5 Results

This section provides the estimation results for the models presented above. In Table 2.3 we begin with a detailed overview of the results drawn from a simple probit estimation of Equation 2.1. The left column refers to the basic specification (specification 1) which does not account for personal traits, the middle part correspond to the five-factor specification (specification 2), and the right part shows the estimation results for the alternative risk specification (specification 3). Table 2.4 presents the estimation results for the bivariate ordered probit model that takes potential endogeneity of SAH into account.

### 2.5.1 Health

With respect to the crucial difference in premium calculations between SHI (income-related premiums) and PHI (risk-adjusted premiums), we would expect individuals in better health to have a higher probability of switching to the private system than individuals in worse health. The estimated coefficients of SAH are jointly significant in all specifications, indicating that health status, which is directly related to premiums under the PHI, affects the inclination to switch from SHI to PHI. Moreover, all point estimates exhibit the expected sign (base category: *satisfactory*). While individuals in very good and good health are more inclined to switch than individuals in satisfactory health, the opposite holds for individuals in poor or bad health. However, the coefficient estimates of the last two categories are jointly insignificant. Apart from higher switching costs due to higher premium amounts, bad risks may have higher opportunity costs of time. That is, instead of figuring out switching opportunities, restoring health by undergoing medical treatments may be their primary objective (Nuscheler and Knaus, 2005). Poorer health status itself, however, may also provide an incentive to switch to PHI, where health care

<sup>16</sup>We use the add-on package `bioprobit` for Stata (Sajaia, 2008). For a detailed description of `bioprobit` see Sajaia (undated). Any data or computational errors are of course our own.

is seen as superior. Yet, bad risks may not switch to PHI due to insufficient financial resources to afford the fairly high premiums under the PHI or simply because they expect to be rejected (Roos and Schut, 2012).

For non-linear models, the raw estimated coefficients do not tell much about the size of the effects under scrutiny. As a first indication of magnitudes, multiplying the estimated coefficients by  $\phi(0) \approx 0.399$  provides an upper bound for the corresponding marginal effects. To get a perspective on the size of the estimates, we consider a simple simulation. Based on the estimation results of specification 2 (including personal traits), switching probabilities are predicted for two counterfactual scenarios. In the first scenario we manually shift individuals' self-reported health to the next higher level. For instance, individuals who reported being in satisfactory health are now assumed to be in good health. The opposite applies to the second scenario, where individuals' self-reported health was shifted to the next lower level.<sup>17</sup> The original values of SAH and the corresponding switching probabilities serve as reference. In this reference scenario, the average predicted probability of switching amounts to 3.60 percent. This rather low figure is explained by the small share of switchers in the sample. Scenario 1 (improved health status) yields an average predicted probability of 4.05 percent. This is an increase of 0.45 percentage points or 13 percent. In scenario 2 (worsened health status), the average predicted probability of switching is 2.97 percent. Compared to the reference, this is a decrease of 0.63 percentage points, which translates to 18 percent. While the absolute changes in the average switching probabilities seem rather low, the relative changes reveal an effect of substantial magnitude.

### 2.5.2 Socioeconomic Characteristics

In line with previous studies (Grunow and Nuscheler, 2014; Federal Ministry of Labour and Social Affairs, 2003), we observe a significant effect of age on the propensity to switch. Age coefficients are jointly significant ( $p$ -value  $< 0.025$ ) in all specifications. Moreover the point estimates display the expected pattern. That is, individuals younger than 40 have the highest inclination to switch to PHI while older individuals aged 50 and over are least likely to opt out of the SHI. Again, this is likely attributable to risk-adjusted premiums which are unattractive for new insureds above a certain age. The latter results may partly stem from the obligation to build up old age provisions under the PHI. The shorter the time span available for building up these provisions is, the higher – *ceteris paribus* – is the premium level in the private system.

The SHI offers free insurance coverage of children aged younger than 25 and of non-working spouses, which makes it attractive for families. In line with this, both the estimated coefficient of the dummy variable of children under 25 and the indicator variable for a non-working spouse exhibit negative signs and are statistically significant. Our result that free insurance coverage of family members is an important reason for staying with the SHI is in accordance with evidence from aggregated data. The Federal Ministry of Health reports that on average a voluntary member has 0.70 dependents covered by family insurance, while a mandatory member has only 0.46. In 2011, roughly 75% of these dependents were aged 25 and younger, suggesting that free insurance coverage of children is more important than of spouses, which does not apply when both spouses are employed.<sup>18</sup>

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<sup>17</sup>Health status was not changed for individuals who reported being in very good health (scenario 1) or bad health (scenario 2). Calculations are based on specification 2, which includes personal traits.

<sup>18</sup>Own calculations based on Federal Ministry of Health (2011).

Table 2.3: Probit Models

|  | Specification 1 |           | Specification 2 |                          | Specification 3 |           |
|--|-----------------|-----------|-----------------|--------------------------|-----------------|-----------|
|  | <i>b</i>        | <i>se</i> | <i>b</i>        | <i>se</i> <sup>(a)</sup> | <i>b</i>        | <i>se</i> |
| SAH ( <i>jointly sig.</i> )                | yes (***)       |           | yes (**)        |                          | yes (***)       |           |
| Very good                                  | 0.196***        | (0.061)   | 0.181**         | (0.075)                  | 0.215***        | (0.064)   |
| Good                                       | 0.131***        | (0.044)   | 0.132**         | (0.053)                  | 0.145***        | (0.046)   |
| Poor                                       | -0.087          | (0.081)   | -0.066          | (0.099)                  | -0.042          | (0.083)   |
| Bad  | -0.374          | (0.236)   | -0.187          | (0.229)                  | -0.262          | (0.234)   |
| Socioeconomic characteristics              |                 |           |                 |                          |                 |           |
| Age 20-29                                  | 0.105           | (0.070)   | 0.043           | (0.090)                  | 0.121*          | (0.073)   |
| Age 30-39                                  | 0.109**         | (0.046)   | 0.090           | (0.056)                  | 0.128***        | (0.048)   |
| Age 50-60                                  | -0.126**        | (0.054)   | -0.126*         | (0.068)                  | -0.127**        | (0.056)   |
| Female                                     | -0.158***       | (0.044)   | -0.135**        | (0.055)                  | -0.133***       | (0.046)   |
| Non-working spouse                         | -0.210***       | (0.069)   | -0.218**        | (0.085)                  | -0.217***       | (0.070)   |
| Children < 25                              | -0.170***       | (0.040)   | -0.136***       | (0.048)                  | -0.129***       | (0.042)   |
| Income                                     | 0.004***        | (0.001)   | 0.010***        | (0.002)                  | 0.004***        | (0.001)   |
| Income squared                             | -0.000          | (0.000)   | -0.000**        | (0.000)                  | -0.000          | (0.000)   |
| Education                                  | 0.010           | (0.007)   | 0.008           | (0.009)                  | 0.009           | (0.007)   |
| Civil servant                              | 1.757***        | (0.110)   | 1.676***        | (0.143)                  | 1.768***        | (0.114)   |
| Self-employed                              | 0.939***        | (0.097)   | 0.881***        | (0.134)                  | 0.919***        | (0.100)   |
| White-collar                               | 0.418***        | (0.090)   | 0.341***        | (0.118)                  | 0.409***        | (0.092)   |
| Residence west                             | -0.057          | (0.048)   | -0.064          | (0.059)                  | -0.047          | (0.050)   |
| German                                     | -0.112          | (0.081)   | -0.042          | (0.112)                  | -0.085          | (0.089)   |
| Personal traits ( <i>jointly sig.</i> )    |                 |           |                 |                          |                 |           |
|  |                 |           | yes (*)         |                          |                 |           |
| Neuroticism                                |                 |           | -0.005          | (0.003)                  |                 |           |
| Openness                                   |                 |           | 0.000           | (0.003)                  |                 |           |
| Extraversion                               |                 |           | 0.009***        | (0.003)                  |                 |           |
| Agreeableness                              |                 |           | -0.001          | (0.002)                  |                 |           |
| Conscientiousness                          |                 |           | 0.001           | (0.003)                  |                 |           |
| Risk-loving                                |                 |           |                 |                          | 0.106***        | (0.039)   |
| Further controls                           |                 |           |                 |                          |                 |           |
| Fixed time effects ( <i>jointly sig.</i> ) | yes (***)       |           | yes (***)       |                          | yes (***)       |           |
| Time at risk ( <i>jointly sig.</i> )       | yes (***)       |           | yes (***)       |                          | yes (***)       |           |
| Awareness                                  | 0.246***        | (0.047)   | 0.246***        | (0.059)                  | 0.254***        | (0.050)   |
| Extended                                   | 0.069           | (0.063)   | 0.099           | (0.074)                  | 0.078           | (0.065)   |
| Left-censored                              | -0.182***       | (0.045)   | -0.152***       | (0.055)                  | -0.179***       | (0.046)   |
| Constant                                   | -2.263***       | (0.164)   | -2.468***       | (0.361)                  | -2.326***       | (0.175)   |
| # Observations                             | 20,244          |           | 14,945          |                          | 19,115          |           |
| # Individuals                              | 5,980           |           | 3,967           |                          | 5,390           |           |
| # Switchers                                | 785             |           | 538             |                          | 727             |           |

Notes: Standard errors are clustered at the individual level; <sup>(a)</sup> bootstrapped standard errors, based on 250 replications. \*\*\* significance at 1%; \*\* significance at 5%; \* significance at 10%.

Overall, we observe a strong effect of occupation on the choice of insurance type. The positive and highly significant coefficient estimate of civil servants is in line with expectations. While on principle civil servants can choose between both systems, they lose entitlements to an additional allowance if insured under the SHI. This creates an exceptionally strong financial incentive to buy private insurance.<sup>19</sup> The results also suggest that self-employed people have a higher inclination to switch to PHI than white- and blue-collar workers (base category). One reason for this observation might be the degree of flexibility under the PHI. The possibility to influence PHI premiums when earnings are

<sup>19</sup>In order to ensure that the results are not driven by the strong financial incentives facing civil servants, we also estimate the model excluding civil servants, which does not change the results.

low and unstable may be especially attractive for self-employed people, who are usually subject to the maximum premium amount under the SHI.<sup>20</sup>

Apart from civil servants and self-employed individuals who are able to switch irrespective of their annual earnings, employees are eligible for PHI only if their annual wage income exceeds the relevant threshold. However, premiums in the SHI are capped just above the current social security contribution ceiling and do not rise for individuals who earn substantially above this threshold. That is, all voluntarily insured employees, except civil servants with income under the social security contribution ceiling, pay the same (maximum) premium amount. Hence, one would expect income to have no significant effect on the inclination to switch to PHI. Nevertheless and as indicated by the significant and marginally significant coefficient estimate of income and its second polynomial respectively, we observe a positive – but decreasing – effect of income on the decision to switch. One explanation for this could be that quality of health care is a normal good, thus has a positive income effect (Besley et al., 1999; Costa and Garcia, 2003). Assuming that PHI offers access to better medical care, which is frequently claimed in public debates and to some extent confirmed by research (Lüngen et al., 2008; Gruber and Kiesel, 2010; Hulleger and Klein, 2010), the inclination to switch would rise when income increases. One may argue, the PHI not only offers comprehensive health insurance but also optional additional cover to those statutorily insured, granting access to services that are not part of the SHI's benefit package. However, extended insurance cover by private supplementary insurance is unlikely to be regarded as perfect substitute to comprehensive private insurance. For instance, waiting time for doctor visits, to which most frequently is referred with respect of discrimination against statutorily insured patients, cannot be reduced via supplementary insurance. For this reason, substitutive PHI might be considered as some sort of status symbol as it is reserved for only certain subgroups of the population.

For the considered period (1997-2010), gender was a key determinant in calculating risk-adjusted premiums. Higher health-related expenditures for women, for instance due to higher life expectancy, led to higher risk-adjusted premiums as compared to men. The estimated coefficient of *female* is highly significant in all specifications and indicates a lower tendency to switch for women. In March 2011, the European Court of Justice ruled that insurers must offer gender-free premiums as of December 21, 2012. This could also have had an impact on the switching probability for women, as those who anticipated this amendment may have postponed their switch until after the law came into effect. Finally, we observe no significant effect on the inclination to switch of education, nationality, or residence.

### 2.5.3 Personality Traits

Accounting for personal traits (specification 2 and specification 3) does not change the previous results in qualitative terms. The five estimated coefficients are jointly significant ( $p$ -value: 0.0894), yet this is driven by the single coefficient of extraversion. In line with the conclusion drawn by Thomson and Mossialos (2006), the coefficient estimate of extraversion exhibits a positive sign. Extraverts are characterized, among others facets, by a positive attitude towards risk. Risk-averse individuals, who also

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<sup>20</sup>In general, under the SHI self-employed – analogous to paid employees – are eligible for adjustment of premiums to reduced income. However, unlike paid employees whose contributions are automatically adjusted to changes in wage earnings, they have formally to apply for premium reductions, for instance, by means of a tax assessment notice. Moreover, irrespective of actual income, self-employed people are subject to a substantial minimum premium.

score low on extraversion, may prefer the SHI for at least two reasons. First, income-related premiums under the SHI provide an indirect way to insure against income-risks. Second, free insurance coverage of dependents may also be an attractive feature for those without dependents but with uncertainty about their future family composition. Risk-averse individuals may also switch less often as health care is an experience good and individuals have better information on the quality of their current public insurance provider than on the quality of its private counterpart (Strombom et al., 2002). Considering specification 3, which includes the alternative measure for risk-loving, the conclusion does not change with respect to the effect of attitude towards risk. Again, the coefficient estimate is positive and significant. The results concerning personal traits other than risk attitude are less conclusive. Therefore, we approximate the effect size only for attitude towards risk.<sup>21</sup>

To obtain a first idea of the effect size, we estimate the average marginal effect of extraversion using specification 2. A one unit increase in extraversion, which translates into one tenth of a standard deviation, increases the probability of switching by 0.06 percentage points on average. In relation to the average probability of switching (3.60 percent), this is a rise of 2.2 percent. Using specification 3, which includes the binary indicator for risk-loving, we estimate average switching probabilities in two counterfactual scenarios. The first assumes all individuals to be risk-averse, while all individuals are assumed to be risk-loving in the second scenario. The difference in the average inclination to switch between both scenarios amounts to 0.76 percentage points, equivalent to an increase of 21 percent. Taken together, these calculations reveal an effect of considerable magnitude of attitude towards risks on the probability to opt out of the SHI.

#### 2.5.4 Further Controls

Figure 2.1 shows a comparison of the estimated coefficients of calendar time (solid line), which are jointly significant ( $p$ -value  $< 0.01$ ), to the annual percentage change in PHI members (dashed line). The latter is calculated from aggregated data based on annual reports by the private insurance business (Association of German private healthcare insurers, 2009, 2012) and is expected to react to major changes in legislation. The sample period covers two substantial changes in legislation that further restrict opportunities for employees to switch to PHI. In 2003 the income threshold was raised substantially by 13%. After 2007, income had to exceed the relevant threshold in three successive years, while it had to exceed the threshold only in the previous year prior to 2007.<sup>22</sup> The peaks in 2001/2002 and 2006 can be explained by earlier switches of individuals who would have been affected by these reforms. The increase from 2007 to 2009 might be attributable to the introduction of a general obligation to obtain insurance coverage, which came into effect by 2009.<sup>23</sup> The similar pattern of the estimated fixed time effects and the annual change in PHI members in Figure 2.1 suggests that the set of yearly dummies captures variation in the probability of switching due to exogenous shocks. Hence, we are confident that the results are not influenced by changes in the regulatory framework.

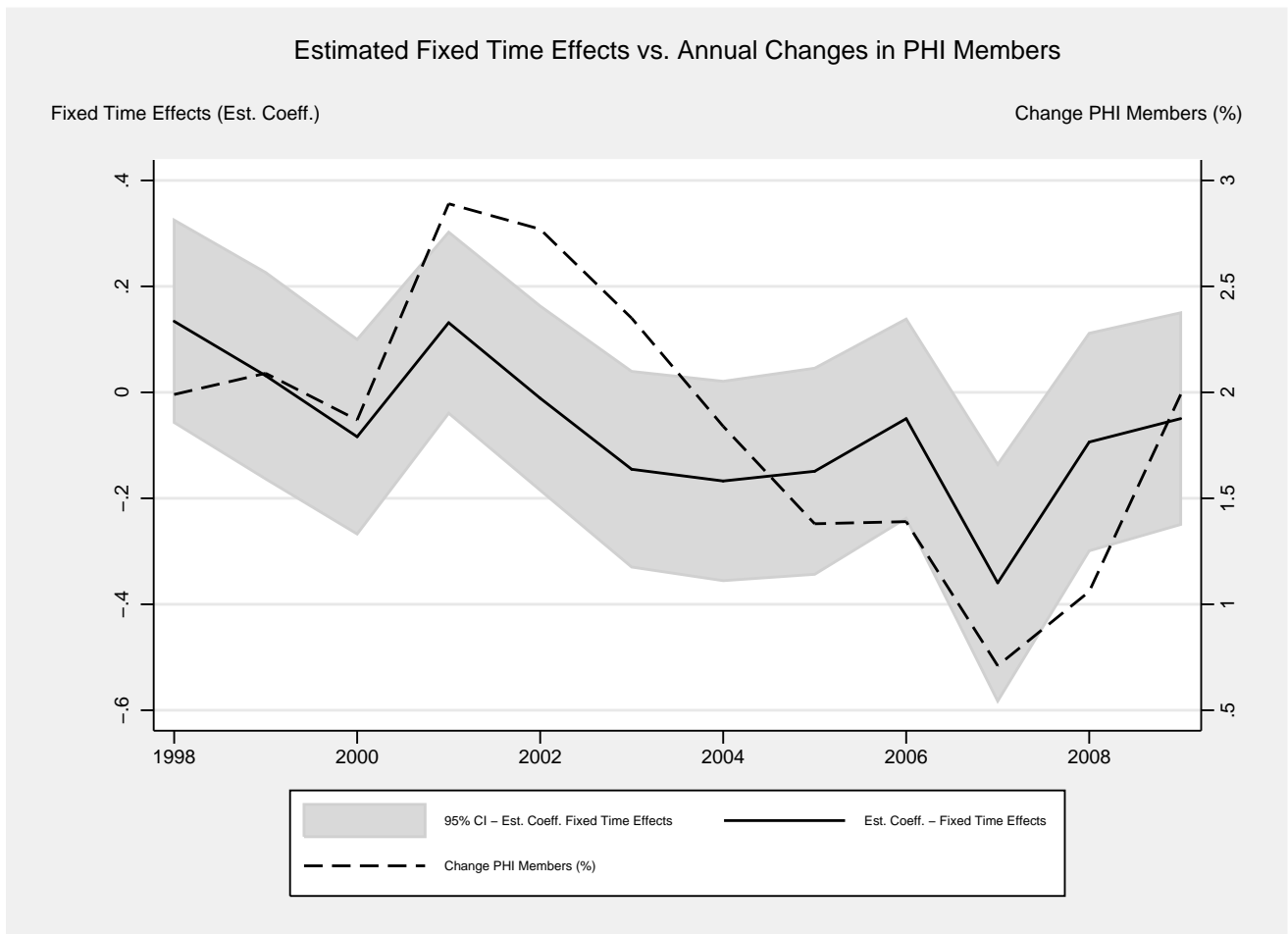
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<sup>21</sup>We also perform a sensitivity analysis using the information from the BFI-S of 2005 instead of 2009 to construct the five measures of personality. This does not affect the results in qualitative terms. Results are available upon request.

<sup>22</sup>As of January 2011, the “three-years-rule” was replaced by the former regulation, i.e. income now has to exceed the relevant threshold only in the previous year.

<sup>23</sup>Deutsche Rückversicherung AG (2010), a large private re-insurance company in Germany, reports in their annual report of 2009 a “pleasing rise of 3.8% in premium income in private health insurance” due to the legal regulations.

Figure 2.1: Fixed Time Effects

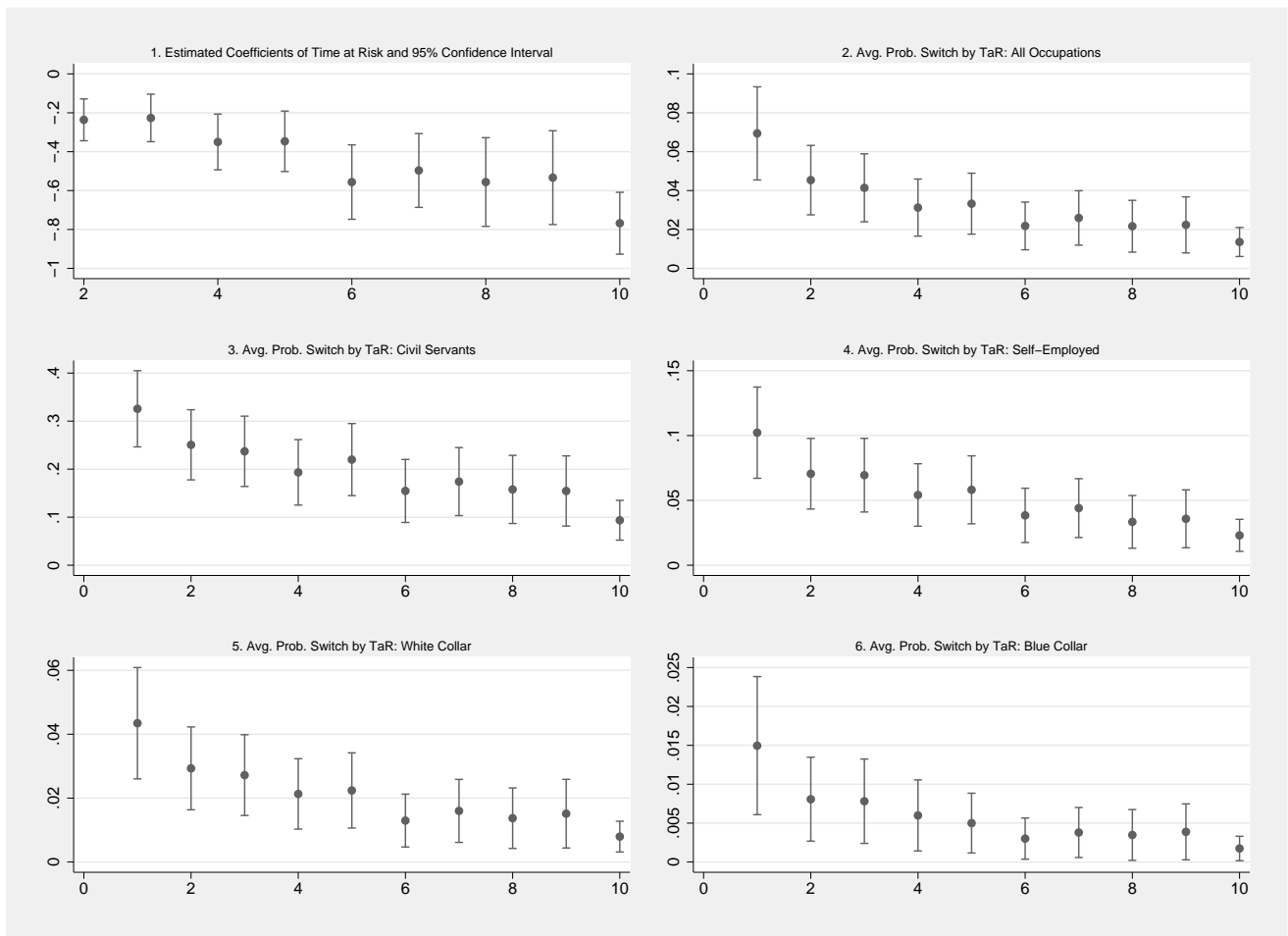


*Notes:* Own calculations based on the SOEP. The figure shows the estimated coefficients of the set of fixed time effects (solid line) and the corresponding 95% confidence interval. Calculation of annual changes in PHI members (dashed line) is based on annual reports by the private insurance business (Association of German private healthcare insurers, 2009, 2012). Data are plotted with linear interpolation superimposed.

Figure 2.2 presents the estimated coefficients of *time at risk* (graph 1) and the relationship between *time at risk* and the average predicted probability to switch by occupational group (graphs 2-5). The estimated coefficients of *time at risk* are jointly significant ( $p$ -value < 0.0001) and show the expected negative trend, indicating that individuals tend to switch as soon as they have the opportunity. As suggested by the absolute magnitude of the estimated coefficients, graphs 2-5 exhibit substantive differences between average predicted switching probabilities across the different cells of *time at risk*. Moreover, similar patterns of graphs 3-5 indicate that these differences – in relative terms – are quite stable across occupational groups. For instance, switching probabilities have almost halved, on average, after being five years at risk. As discussed in section 2.3, individuals who are willing to leave the SHI are likely to switch as soon as possible. Early switching provides more time to build up the obligatory old age provision, and hence reduces the premium amount. In line with this, we also observe a negative and significant estimate for *left-censored*, suggesting a lower probability to switch. This is reasonable as these individuals have been longer at risk than indicated by the relevant indicators, as they were already at risk when they entered the sample.



Figure 2.2: Time at Risk



Notes: Own calculations based on the SOEP. Graph 1 shows the estimated coefficients for “Time at Risk” and the corresponding 95% confidence intervals. Graphs 2-6 show the average predicted probabilities and the corresponding 95% confidence intervals by “Time at Risk” separated by occupational groups (2: all occupations; 3: civil servants; 4: self-employed individuals; 5: white-collar workers; 6: blue-collar workers).

To investigate the effect of awareness, i.e. whether or not an individual is aware of her opportunity to leave the SHI, we include an indicator variable. The estimated coefficient of *awareness* is positive and highly significant. However, this should not be interpreted as causal, as individuals who would not consider leaving the SHI are not likely to invest any effort in researching switching options. Finally, the estimated coefficient for individuals who entered the sample only through reported insurance status (*extended*) is insignificant.<sup>24</sup>

### 2.5.5 Potential Endogeneity of Self-Assessed Health

In order to ensure that the above-mentioned results are not driven by potential endogeneity of self-assessed health, we also adopt an instrumental variable approach similar to Grunow and Nuscheler (2014). Table 2.4 reports the estimation results using the bivariate ordered probit model, where we consider two sets of explanatory controls. The first two columns refer to the five factor specification (specification 2), whereas the last two columns display the results of the alternative risk specification

<sup>24</sup>We also perform a sensitivity analysis which excludes these observations, which does not affect the results in qualitative terms. Results are available upon request.

Table 2.4: Bioprobit Models

|   | Specification 2 |                          |                  |                          | Specification 3 |           |            |           |
|---|-----------------|--------------------------|------------------|--------------------------|-----------------|-----------|------------|-----------|
|   | Health Eq.      |                          | Switch Eq.       |                          | Health Eq.      |           | Switch Eq. |           |
|   | <i>b</i>        | <i>se</i> <sup>(a)</sup> | <i>b</i>         | <i>se</i> <sup>(a)</sup> | <i>b</i>        | <i>se</i> | <i>b</i>   | <i>se</i> |
| SAH                                     |                 |                          | -0.408***        | (0.146)                  |                 |           | -0.348***  | (0.122)   |
| Socioeconomic characteristics           |                 |                          |                  |                          |                 |           |            |           |
| Age 20-29                               | -0.422***       | (0.057)                  | -0.116           | (0.114)                  | -0.414***       | (0.048)   | -0.001     | (0.092)   |
| Age 30-39                               | -0.255***       | (0.035)                  | -0.010           | (0.072)                  | -0.238***       | (0.031)   | 0.056      | (0.058)   |
| Age 50-60                               | 0.237***        | (0.037)                  | -0.021           | (0.079)                  | 0.199***        | (0.033)   | -0.051     | (0.064)   |
| Female                                  | 0.000           | (0.042)                  | -0.136**         | (0.057)                  | 0.034           | (0.033)   | -0.124***  | (0.047)   |
| Non-working spouse                      | 0.016           | (0.043)                  | -0.197**         | (0.087)                  | -0.004          | (0.035)   | -0.207***  | (0.068)   |
| Children < 25                           | 0.048           | (0.038)                  | -0.119**         | (0.052)                  | 0.027           | (0.031)   | -0.123***  | (0.042)   |
| Income                                  | -0.003***       | (0.001)                  | 0.008***         | (0.003)                  | -0.003***       | (0.001)   | 0.003***   | (0.001)   |
| Income squared                          | 0.000           | (0.000)                  | -0.000**         | (0.000)                  | 0.000***        | (0.000)   | -0.000     | (0.000)   |
| Education [years]                       | -0.022***       | (0.006)                  | -0.001           | (0.010)                  | -0.027***       | (0.006)   | 0.001      | (0.008)   |
| Civil servant                           | -0.356***       | (0.099)                  | 1.457***         | (0.213)                  | -0.334***       | (0.091)   | 1.615***   | (0.163)   |
| Self-employed                           | -0.198***       | (0.054)                  | 0.755***         | (0.139)                  | -0.173***       | (0.048)   | 0.832***   | (0.113)   |
| White-collar                            | -0.116**        | (0.047)                  | 0.276***         | (0.105)                  | -0.125***       | (0.039)   | 0.356***   | (0.095)   |
| Residence west                          | -0.075*         | (0.038)                  | -0.084           | (0.056)                  | -0.122***       | (0.036)   | -0.079     | (0.051)   |
| German                                  | 0.197**         | (0.083)                  | 0.051            | (0.114)                  | 0.116*          | (0.062)   | -0.044     | (0.089)   |
| Personal traits ( <i>jointly sig.</i> ) |                 |                          |                  |                          |                 |           |            |           |
| Neuroticism                             | 0.022***        | (0.004)                  | yes(**)          |                          |                 |           |            |           |
| Openness                                | -0.002          | (0.002)                  | 0.003 (0.004)    |                          |                 |           |            |           |
| Extraversion                            | -0.004          | (0.004)                  | 0.007*** (0.003) |                          |                 |           |            |           |
| Agreeableness                           | -0.007***       | (0.002)                  | -0.004* (0.002)  |                          |                 |           |            |           |
| Conscientiousness                       | -0.005***       | (0.002)                  | -0.001 (0.003)   |                          |                 |           |            |           |
| Risk-loving                             |                 |                          |                  |                          | -0.105***       | (0.030)   | 0.072*     | (0.043)   |
| Further controls                        |                 |                          |                  |                          |                 |           |            |           |
| Time effects ( <i>jointly sig.</i> )    |                 |                          | yes(***)         |                          |                 |           | yes(***)   |           |
| Time at risk ( <i>jointly sig.</i> )    |                 |                          | yes(***)         |                          |                 |           | yes(***)   |           |
| Awareness                               | 0.055           | (0.035)                  | 0.251***         | (0.061)                  | 0.086***        | (0.030)   | 0.265***   | (0.049)   |
| Extended                                | 0.001           | (0.038)                  | 0.101            | (0.073)                  | 0.044           | (0.034)   | 0.090      | (0.063)   |
| Left-censored                           | -0.039          | (0.041)                  | -0.159***        | (0.052)                  | -0.055          | (0.033)   | -0.186***  | (0.046)   |
| Instruments ( <i>jointly sig.</i> )     |                 |                          |                  |                          |                 |           |            |           |
| # Hospitalizations                      | 0.071***        | (0.019)                  | yes(***)         |                          | 0.065***        | (0.013)   | yes(***)   |           |
| Disability                              | 0.733***        | (0.074)                  |                  |                          | 0.789***        | (0.067)   |            |           |
| Correlation / <i>p</i> -value           | 0.344 / 0.021   |                          |                  |                          | 0.274 / 0.030   |           |            |           |
| # Observations                          | 14,885          |                          |                  |                          | 19,027          |           |            |           |
| # Individuals                           | 3,963           |                          |                  |                          | 5,378           |           |            |           |
| # Switchers                             | 535             |                          |                  |                          | 722             |           |            |           |

Notes: Standard errors are clustered at the individual level; <sup>(a)</sup> bootstrapped standard errors, based on 250 replications. \*\*\* significance at 1%; \*\* significance at 5%; \* significance at 10%.

(specification 3).<sup>25</sup> With respect to the instrumental equation, a test on instruments relevance turns out highly significant in both specifications. Hence, we are not concerned about weak instruments. Considering the switching equation, the results, and in particular the estimated coefficient of SAH, are very close to what we find in the simple probit model. However, this does not hold fully for the estimated coefficients of age, which are no longer significant. The loss of significance in some estimated coefficients, most notably age, may be attributable to fewer restrictions and in consequence larger standard errors in the bivariate ordered probit model. The estimated correlations between the equations' error terms are positive and significant in both specifications (*p*-values: 0.021 / 0.030), indicating endogeneity of SAH. The positive sign of the estimated coefficient suggests that unobservable factors lead

<sup>25</sup>Similar results of the basic specification are not reported.

to lower reported health and a higher inclination to switch. This counterintuitive result might be explained by an expected quality gap in favor of the PHI, which might attract especially individuals who are more concerned about their health. Overall, the qualitative conclusions drawn from the simple probit regression still hold.

Finally, there might be concerns about the instruments used in this analysis. While SAH presumably reflects both private and public information, hospitalizations and disability are mainly public information. One might argue that individuals with poor health, which is hard to observe for third parties (insurers), might be more inclined to switch to PHI – where services are perceived as better – than those individuals whose health is poor but observable for insurers. However, withholding relevant information – private or public – may cause severe problems for insurance holders. In the most extreme case, insurance holders do not only lose their insurance coverage but have to reimburse payments already made by the insurer. Since this is well-known, applicants have a strong incentive not to cheat upon concluding the contract.

## 2.6 Conclusion

Based on data from the SOEP, this paper analyzes incentives to switch from public to private health insurance in Germany. In order to account for the various regulatory conditions and related incentives, a comprehensive set of explanatory variables is used. We include health status, age, and gender to capture the effect of risk-adjusted premiums under the PHI; family characteristics to control for free insurance coverage of dependents under the SHI; and we account for specific incentives due to occupation through a set of dummies. To investigate the previously unconsidered role of personality, five personal traits, including measures for risk-aversion and altruism, enter the model. Moreover, since individuals who are willing to leave the SHI tend to switch as soon as they have the opportunity, we control for the duration for which an individual has been able to opt out.

Applying a hazard model in discrete time and accounting for potential endogeneity of self-assessed health through an instrumental variable approach, the estimation results yield robust evidence that individuals typically opt out of the SHI and chose substitutive PHI for economic reasons. For instance, the SHI is preferred by individuals who benefit from free insurance coverage of dependents or by those who are discouraged by risk-adjusted premiums under the PHI, i.e. bad health risks. Moreover, the present analysis provides convincing empirical evidence for the notion that attitude towards risk also affects the choice of insurance type. Risk-loving individuals have a significantly higher probability of buying private health insurance than those who are risk-averse, with simulations revealing an effect of considerable size. With respect to the remaining personality traits considered in this analysis, the results are less conclusive. In particular, we observe no significant effect of the measure of altruism on the decision to opt out of the SHI. This implies that staying under the SHI cannot be regarded as a statement of solidarity, but rather as a result of pragmatic, benefit-maximizing behavior. In turn, this result challenges the notion of a broad societal acceptance of the SHI's solidarity principal even among those who do not directly benefit from redistribution within the SHI. The coexistence of SHI and PHI, subject to an sometimes ideological debate in German politics during the recent years, seems to be a less emotional issue from the insureds' perspective, at least among those who can choose. This may be taken as a call for a less fevered policy debate that focuses on the question of how to design

a regulatory framework that allows for more competition between both systems rather than on the question of which system, as a matter of principle, is the more desirable one.

This paper also complements and confirms the key finding of Grunow and Nuscheler (2014) that risk-segmentation in favor of the PHI is present in the German health insurance system. Our analysis also finds that young, healthy, and high-earning individuals are more likely to leave the public system. This generates several problems for the health insurance system in Germany. First, since contributions of potential switchers typically correspond to the maximum premium amount under the social health insurance scheme, generating positive marginal returns for the SHI, advantageous selection into the PHI may further increase financial pressure on the former, which is already severely affected by demographic change. Second, to prevent individuals from opting out, statutory sickness funds may adapt their offers to the needs of relatively few potential switchers. However, these needs may not be in line with those of the majority of compulsory members. This is likely to result in an inefficient allocation of resources in the German health system.

## Chapter 3

# How Health Plan Enrollees Value Prices Relative to Supplemental Benefits and Service Quality

### 3.1 Introduction

Health plan literacy has become a buzzword in the current health care debate. It refers to the provision of extensive information and education on health care and health plans, in addition to a set of available choices. Theory postulates that a high degree of health care literacy leads to behavioral changes – e.g., health plan switching – which would make the market more efficient and improve quality. Increasing consumer health literacy is generally seen as a promising road to gradually improving the efficiency and quality of health care systems around the world. Yet it remains controversial to what extent consumers are already using available information when making important choices, for example in choosing health plans.

Health plan choice essentially depends on the factors (i) price – typically a non-linear trade-off between premiums and cost-sharing amounts – , (ii) benefits covered, (iii) clinical health care quality – e.g., via provider networks or managed care – as well as the (iv) service quality of the insurer. Empirically estimating the impact of these four factors is challenging, particularly in the US setting where we observe a fragmented health care landscape with hundreds of thousands of different health plan parameters. Most US employees are limited to a choice of two or three plans – mostly being HMO or PPO – making it challenging to disentangle the generalizable impact of single determinants. That being said, most empirical studies on health plan choice determinants exploit the US setting (Dowd and Feldman, 1994; Cutler and Reber, 1998; Royalty and Solomon, 1999; Strombom et al., 2002; Atherly et al., 2004; Buchmueller, 2006; Buchmueller et al., 2013). In single payer markets such as Canada or

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This study is joint work with Hendrik Schmitz, Harald Tauchmann and Nicolas R. Ziebarth. See Bünnings et al. (2015) for a working paper version of this chapter.

the UK, people do not have any choice with regard to their health plans. This limitation explains the absence of empirical studies on the determinants of health plan choice for these countries.

This study focuses on the German case which is, for several reasons, a particularly interesting one to analyze. The German statutory health insurance (SHI) represents a “third way” between government run single payer systems without any choice and the US, where health care is pre-dominantly offered through less regulated private entities. Although the US system has moved towards an increasingly regulated system under the Affordable Care Act (ACA) (or *ObamaCare*), the German market is still more heavily regulated and standardized. However, Germany combines this heavy regulation with a relatively high degree of health plan choice. In the German SHI, about 130 sickness funds (=health plans<sup>1</sup>) compete for mostly mandatorily insured customers. Most of these health plans operate nationwide although several are solely offered in some of the 16 German states. An interesting feature of the German health care market is that, unlike the US, managed care is legally prohibited. Furthermore, selective contracting does not exist. This implies the absence of provider networks and the uniformity of reimbursement rates leads to uniformity of clinical health care quality across all 130 health plans. Providers do not know or care about patients’ SHI sickness funds, which eliminates the relevance of health plan determinant (*iii*) above – variation in health care quality. German social legislation also prohibits deductibles and coinsurance rates and only allows small copayments for inpatient and outpatient care. Those small copayments for inpatient and outpatient care do not vary across plans either.<sup>2</sup> This regulation shuts down the non-linear trade-off between premiums and cost-sharing in factor (*i*) above. Finally, German social legislation establishes a very generous “essential benefit package” similar to the one under the ACA in the US. Essentially all medically necessary inpatient and outpatient treatments are covered.<sup>3</sup> However, sickness funds may “voluntarily” offer the coverage of additional benefits such as alternative treatments or immunizations for tropical diseases to differentiate their product.

This study empirically exploits the standardization and the extensive health plan choice set in the German market. We link representative enrollee panel data to publicly available health plan prices, as well as standardized health plan quality information, and exploit changes in these health plan characteristics across 115 plans and over 4 years. We exploit standardized supply-side information from a well-respected private company that consistently surveys and ranks all German health plans. Thus, our empirical approach exploits the same standardized supply side information that German consumers can access in online portals and magazine rankings in order to select health plans.

This paper estimates the impact of the three health plan choice parameters (*i*) price, (*ii*) “non-essential” supplemental benefits, and (*iii*) service quality on the decision to select health plans. *Service quality* is mostly defined by health plan accessibility (via physical branches, hotlines or the internet) and the quality of information provided to customers looking for help. While a substantial body of empirical literature analyzes the price impact of health plan choice<sup>4</sup> (e.g. Strombom et al., 2002; Atherly et al., 2004; Schut and Hassink, 2002; Buchmueller, 2006; Tamm et al., 2007; Frank and Lamiraud, 2009; Buch-

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<sup>1</sup>We use the terms “health insurance (company),” “sickness fund,” and “health plan” as interchangeably.

<sup>2</sup>For the time period under consideration, the copayments were 10€ (\$13) per day for a hospital day as well as 10€ per calendar quarter for outpatient visits. Total cost-sharing is capped at 2% of the annual income, for chronically ill at 1%.

<sup>3</sup>As in other countries, the coverage of dental care and eyeglasses is limited.

<sup>4</sup>Overviews are provided by Kolstad and Chernew (2009) and Gaynor and Town (2012).

mueller et al., 2013; Schmitz and Ziebarth, 2011; Wuppermann et al., 2014) there exist only a few studies on the role of benefits and quality.

Using employer data from General Motors and accounting for health plan fixed effects, Scanlon et al. (2002) estimate changes in health plan market shares due to the introduction of quality report cards. They observe that employees avoid subscribing to health plans with below average ratings. Chernew et al. (2008) use the same data and apply a Bayesian learning model to show that only 3% of enrollees switch health plans due to report cards. Estimating a cross-sectional conditional logit model on health plan choices of Harvard employees, Beaulieu (2002) finds a positive relationship between higher quality ratings and the probability of health plan choice. And exploiting data on federal US employees, Wedig and Tai-Seale (2002) use a nested multinomial logit model to show how these report cards increase price elasticity. Harris (2002), in contrast, conduct a discrete choice experiment in West Los Angeles and conclude that large quality differences would be required for consumers to accept provider access restrictions. Dafny and Dranove (2008) analyze the response of federal retirees to public quality ratings while controlling for market-based learning and find that both public and nonpublic information play a modest role in health plan decision making.<sup>5</sup> Finally, Abraham et al. (2006) do not find that information about higher-quality alternatives affects switching behavior.

This paper is one of the rare studies on the determinants of health plan choice – in particular when taking into account health plan benefits and services – outside the US. Linking representative individual-level health plan switching information from the German Socio-Economic Panel Study (SOEP) to detailed objective health plan data from 2007 to 2010, this paper investigates the relative roles of prices, non-essential benefits, and service quality. As discussed, by construction, the German institutional framework eliminates important confounding channels such as additional non-linear variation in cost-sharing dimensions or differences in provider networks and reimbursement rates and thus, perhaps most importantly, health care quality (Ziebarth, 2012; Gruber and McKnight, 2014). A major strength of our analysis is that we are able to reproduce an almost complete picture of each enrollee's SHI health plan choice set and are not restricted to single regions, employers or certain subgroups of the population. The empirical specifications employ mixed logit models that take heterogeneity in individual preferences as well as unobserved health plan characteristics into account. Our findings show a significantly negative price effect on health plan choice but no indication that supplementary benefits and service quality play an important role in the decision to choose health plans. Heterogeneity analyses with respect to individuals' age, gender and health status indicate that only modest effect heterogeneity exists in this market.

The remainder of the paper is organized as follows: The next section covers the institutional details of the German health insurance market. Section 3.3 outlines the empirical specification and section 3.4 presents the data used for estimation. The estimation results are presented in section 3.5. Section 3.6 concludes.

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<sup>5</sup>This is in line with Jin and Sorensen (2006) who exploit public and nonpublic health plan ratings and find evidence that both influence individuals' decisions but only moderately.

## 3.2 Institutional Background

The German health insurance system is characterized by the coexistence of statutory health insurance (SHI) and substitutive private health insurance (PHI). This paper focuses on the SHI, which covers roughly 90% of the population most of whom are compulsorily insured. Insurance under the SHI is mandatory for employees with gross wage earnings below a defined threshold (in 2014: 53,550 € per year). Nonworking spouses and dependent children under 25 years are covered at no additional costs by SHI family insurance. Further regulations also apply to specific groups of the population, such as students and the unemployed, although most of them are covered by SHI. High-income employees, self-employed individuals and civil servants may opt out of the SHI and buy substitutive PHI or stay under the SHI as voluntary members. Currently the SHI market comprises around 130 not-for-profit health insurance companies, also called “sickness funds”, roughly half of which are operating nationwide, while the remaining ones solely operate in some federal states. Switching sickness funds is uncomplicated: the minimum contract period is 18 months and there is no enrollment period; guaranteed issue exists and several specific search engine websites help consumers to compare and switch health plans.<sup>6</sup> Yet, health plan switching is a rare event among SHI enrollees. In a given year only about 5% of all SHI insured switch health plans (Schmitz and Ziebarth, 2011).

About 95% of the SHI benefit package is predetermined by social legislation at the federal level. The federally mandated minimum benefit package is very generous relative to international standards, basically including all medically necessary treatments in addition to prescription drugs, birth control, preventive and rehabilitation care as well as rest cures (cf. Ziebarth (2010a)). Albeit more generous, this minimum benefit package is comparable to the new Essential Health Benefits under the ACA. However, German social legislation additionally heavily restricts cost-sharing such that only small copayments exist that are identical across health plans. Yet, to differentiate their product and attract enrollees, sickness funds have the opportunity to voluntarily offer additional benefits, which are not part of standard package under the SHI. These **optional supplemental benefits** can be subdivided into (i) alternative medicine and (ii) further supplementary benefits.

*Alternative medicine* covers complementary treatments such as ayurveda, homeopathy, osteopathy, and urine therapy.<sup>7</sup> Although the effectiveness of alternative medicine is discussed controversially, demand for such treatments seems to be increasing. Along with these alternative medical treatments, sickness funds may also offer conventional “non-essential” medical treatments. Examples for these *supplemental benefits* could be preventive check-ups (e.g. the “J2” check-up for adolescents) and certain types of immunizations (e.g. malaria prophylaxis). Typically these benefit differences result only in very small expenditure differences, e.g., a single combined vaccination shot against diphtheria and typhoid fever costs about 15 €. However, supplemental benefits may also comprise more expensive medical treatments, such as additional subsidies for in-vitro fertilizations. However, these more expensive supplemental benefits usually solely apply to a very small group of enrollees.

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<sup>6</sup>The minimum contract period for those who are subscribed in special health plans (“optional tariffs”) ranges from one to three years. If sickness funds plan to increase prices, insureds have – independent of the enrollment length – an extraordinary right to cancel the contract and switch funds.

<sup>7</sup>More precisely, sickness funds are allowed to provide alternative medical treatments only if they fulfill the efficiency principle. According to the German Social Code Book V (paragraph 12), treatments fulfill this principle if they are sufficient as well as medically and economically appropriate, which is, however, a rather vague legal concept.



**Health plan premiums** are calculated in form of social insurance contributions. To calculate the employee share of the premium, a sickness fund specific contribution rate is applied to the gross wage, including all fringe benefits, up to a defined contribution ceiling (in 2014: 48,600€ per year). One half of the contribution rate is formally paid by the employee and the other half by the employer. In January 2009 and as part of a health policy reform (*GKV-Wettbewerbsstärkungsgesetz*), SHI financing was reorganized. Prior to January 2009, health insurance premiums were a function of gross wage earnings and the contribution rate. The latter was set independently by each sickness fund, resulting in a variety of contribution rates, ranging from 12.2 to 16.9% of individual's gross wage earnings in 2008. The reform equalized the contribution rates to 15.5% across all health plans.<sup>8</sup> After 2009, if allocated revenues from the 15.5% standardized contribution rate did not cover the health plan's expenses, sickness funds had to charge an additional premium in form of an absolute monthly Euro amount from their members. If allocated revenues exceeded expenses, sickness funds could pay out a bonus to their members. Hence, post reform, price differences were expressed in absolute rather than relative terms, which increased switching behavior significantly (Schmitz and Ziebarth, 2011; Wuppermann et al., 2014). However, we convert all monthly health plan premiums for each enrollee into euro amounts. Moreover, section 3.5.4 looks at potential influences of the reform on the sickness fund choice behavior.

Apart from price and benefit differentiation, sickness funds compete on **service quality**. We define service quality as the general accessibility and the quality of information provided to enrollees. Most sickness funds operate a network of physical branches but also offer hotline services. Running a large number of branches may be preferable to (some) members – e.g., the elderly – but also implies higher operational costs. In order to reduce administrative expenditures, some sickness funds reduced their branch network significantly over time. A minority of sickness funds do not run any physically accessible branch but are exclusively available by telephone or the internet (“Direktversicherer”). Improved accessibility by phone or the internet was also enforced by the health care reform of 2000 (*GKV-Gesundheitsreformgesetz*). According to this legislation, all sickness funds had to improve their service and consulting. As a result, health plans started to operate different types of hotlines. While some were general, aimed to help insurance members with questions related to membership issues, others provided more detailed information, such as information about drugs and their side effects.

### 3.3 Empirical Specification

Following the contemporary literature that investigates the effect of health plan's characteristics on health plan choice (e.g. Beaulieu, 2002; Wedig and Tai-Seale, 2002; Jin and Sorensen, 2006; Dafny and Dranove, 2008), we apply discrete choice methods. More precisely, we opt for a random parameters model (Revelt and Train, 1998; McFadden and Train, 2000). The random parameters model (RPL), also called mixed logit model, is a generalization of the conditional logit model (McFadden, 1973) and has two important advantages over the traditional conditional logit that makes it especially attractive in the present analysis.

First, several studies (e.g. Beaulieu, 2002) provide indications for the presence of heterogeneity in preferences with respect to health plan characteristics. Considering alternative medicine, for instance, pref-

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<sup>8</sup>Due to the financial crisis, the contribution rate was temporarily decreased to 14.9% from July 2009 to December 2010. Since January 2011, the initial contribution rate of 15.5 percent applies.

erences for such treatments are likely heterogeneously distributed across the population. While some individuals may value such treatments very highly, others may not care about them at all. The mixed logit model explicitly allows for introducing heterogeneity in consumer preferences by modeling the preference parameters as random variables.

Second, the RPL does not rely on the restrictive independence of irrelevant alternatives (IIA) assumption. The IIA assumption requires that the odds between two alternatives do not depend on which other alternatives are available. As individual choice sets consist of a large number of alternatives (health plans) that can be considered as close substitutes, the IIA assumption is at least questionable.<sup>9</sup> We specify the linear index, measuring individual  $i$ 's inclination to choose health plan  $j$  as

$$\gamma_i'Premium_{ij} + \delta_i'Benefits_j + \zeta_i'Service_j + \alpha_j + \varepsilon_{ij} \quad (3.1)$$

$Premium_{ij}$  is the monthly health insurance premium in Euro. The vectors  $Benefits_j$  and  $Service_j$  includes measures for additional benefits and service quality characteristics, which are covered in more detail in the subsequent section. Since the premium is income-dependent – unlike  $Benefits_j$  and  $Service_j$  –  $Premium_{ij}$  varies across individuals and sickness funds. To account for time- and individual-invariant unobservable health plan characteristics that might be correlated with our explanatory variables, we include a set of sickness fund fixed effects ( $\alpha_j$ ). Essentially, we assume that the unobserved part of utility consists of a sickness fund-specific fixed effect and a random error term.<sup>10</sup> If, however, time varying unobservable health plan factors exist that are correlated with the characteristics under scrutiny, endogeneity would still be an issue in our empirical analysis. We assume the  $\varepsilon_{ij}$  to be iid and to follow a type I extreme value distribution and, thus, arrive at the familiar conditional logit model.

The coefficient vectors  $\gamma_i$ ,  $\delta_i$  and  $\zeta_i$  comprise the preference parameters of interest. As indicated by the subscript  $i$ , these preferences are allowed to vary across individuals but are assumed to be constant for the same individual over time. We choose the most common distributional form for the coefficients and assume that individual preferences are normally distributed.<sup>11</sup> Since the likelihood function has no closed-form solution, we apply maximum simulated likelihood methods to estimate the parameters.<sup>12</sup>

Finally, although we have substantial information on individual socio-economic characteristics, we do not directly include them in the model. Considering that they are alternative invariant, including these variables would require interacting them with each alternative in the respective choice set (since we are estimating the relationship between alternative varying characteristics on health plan choice). Yet, individual choice sets are quite large (ranging from 41 to 73 alternatives) in our analysis. An approach that considers socioeconomic characteristics would inflate the number of coefficients enormously and would be impractical for computational reasons.

<sup>9</sup>The IIA assumption is arguably less problematic for studies in the U.S., as choice sets in employer-sponsored settings typically do not comprise more than five alternatives. However, Wedig and Tai-Seale (2002) restrict their estimation sample to choice sets with five or fewer alternatives to make the IIA assumption more plausible. Moreover, Harris (2002) find statistically significant evidence that preference heterogeneity exists, suggesting that the IIA assumption is violated.

<sup>10</sup>This is similar to the approach adopted by Chernew et al. (2004). In general, one could allow the alternative-specific fixed effects to vary across individuals, similar to the other explanatory variables. Due to the large number of alternatives in our choice sets, this would require to estimate distribution parameters of more than 100 additional random variables. Given the already high dimensional optimization problem, this approach is not feasible in the present analysis.

<sup>11</sup>We assume a diagonal variance-covariance matrix of the coefficients, and hence uncorrelated coefficients.

<sup>12</sup>We use the Add-On package `mixlogit` for Stata (Hole, 2007). Estimation results are based on 50 Halton draws. Any data or computational errors are our own.

## 3.4 Data

We make use of two different data sources, which are described in more detail below, and combine them to a dataset that mirrors in detail the health plan choice sets of the SHI insured in Germany.

### 3.4.1 Individual Level Data

Individual-level data is taken from the German Socio-Economic Panel Study (SOEP). The SOEP is a representative longitudinal survey that started in 1984 and collects annual information on both the household and the individual level. Currently, the SOEP comprises more than 20,000 individuals from more than 10,000 households (Wagner et al., 2007). We use the waves 2008 to 2011.

The estimation sample exploits information on enrollees' current sickness fund as well as their insurance status. First, we exclude those individuals who are covered by PHI. Second, we restrict the sample to sickness fund enrollees, not the total number of insured. The latter would also include family members insured at no cost under SHI family insurance. We focus on the paying members so we have exactly one observation per health plan choice decision. Paying members are the insurance holder, gainfully employed and earn more than 400€ gross per month.<sup>13</sup> Third, to ensure that the empirical results are not driven by the high degree of state dependence – as only 5.3% of all individuals switch their health plans – we focus on sickness fund switchers and those who opt out of the family insurance to become a paying member. The intuition behind the latter is that these individuals are likely to inform themselves carefully about their new health plan options. Restricting the sample to 'switchers' is similar to estimating a model that also includes non-switchers and explicitly controls for state dependence. However, due to the large number of alternatives in individuals' choice sets, estimating a mixed logit model that accounts for state dependence is both computationally expensive and instable. Since, in both approaches, the effects are identified by those who switch health plans, we opt for the simpler approach. The final estimation sample consists of 1,726 choices from 1,594 different individuals (that is, about 100 individuals change their sickness fund twice in the observation period).

To construct individual choice sets, we exploit information on the enrollees' state of residence. Since the majority of, but not all, sickness funds operate nationwide it ensures that only relevant health plans enter an individual's choice set. As can be seen in Panel A of Table 3.1, the choice sets include on average 58 sickness funds, ranging from 41 to 73 health plan alternatives. Choice sets are smallest for individuals living in Mecklenburg-Western Pomerania, ranging from 41 different health plans in 2011 to 53 in 2008. Individuals residing in North Rhine-Westphalia have the largest choice sets, ranging from 55 (2011) to 73 (2008).<sup>14</sup> Overall, the empirical identification relies on 400 to 500 observed health plan decisions per year, where each individual has 50 to 60 health plans to chose from. Thus, we annually observe about 25,000 potential options, totaling 100,000 options over the four years under consideration.

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<sup>13</sup>This excludes all those insured under SHI family insurance, the unemployed for some of whom social security pays the health insurance premium, full-time students who just pay an income-independent flat premium (2014: 64,77€ per month) or who are insured under their parents' family insurance, pensioners as well as special population groups, such as draft soldiers or low-income earners.

<sup>14</sup>Due to several mergers of sickness funds, the number of active health plans is decreasing over time.

Table 3.1: Descriptive Statistics

| Panel A: Sample Characteristics        | 2008   | 2009   | 2010   | 2011   | Total  |       |
|--|--------|--------|--------|--------|--------|-------|
| Observations (=choice options)         | 25,920 | 25,476 | 27,352 | 21,140 | 99,888 |       |
| Choice Occasions (=choice sets)        | 388    | 447    | 477    | 414    | 1,726  |       |
| Switchers                              | 231    | 293    | 318    | 285    | 1,127  |       |
| Exit Family Insurance                  | 157    | 154    | 159    | 129    | 599    |       |
| # Alternatives in Choice Sets          |        |        |        |        |        |       |
| Mean                                   | 66.8   | 57.0   | 57.3   | 51.1   | 57.9   |       |
| S.D.                                   | 5.4    | 4.4    | 4.7    | 3.9    | 7.1    |       |
| Min.                                   | 53.0   | 48.0   | 48.0   | 41.0   | 41.0   |       |
| Max.                                   | 73.0   | 63.0   | 63.0   | 55.0   | 73.0   |       |
| Panel B: Individual Characteristics    | Mean   | S.D.   | Med.   | Min.   | Max.   | Obs.  |
| Self-Assessed Health                   | 2.34   | 0.84   | 2      | 1      | 5      | 1,724 |
| Very Good                              | 0.13   | 0.34   | 0      | 0      | 1      | 1,724 |
| Good                                   | 0.49   | 0.50   | 0      | 0      | 1      | 1,724 |
| Satisfactory                           | 0.29   | 0.45   | 0      | 0      | 1      | 1,724 |
| Poor                                   | 0.08   | 0.27   | 0      | 0      | 1      | 1,724 |
| Bad                                    | 0.01   | 0.10   | 0      | 0      | 1      | 1,724 |
| Age                                    | 37.03  | 12.63  | 37     | 18     | 80     | 1,726 |
| Female                                 | 0.55   | 0.50   | 1      | 0      | 1      | 1,726 |
| Monthly Gross Income [EUR]             | 1,959  | 1,413  | 1,700  | 400    | 12,885 | 1,726 |
| Panel C: Sickness Fund Characteristics | Mean   | S.D.   | Med.   | Min.   | Max.   | Obs.  |
| Premium [EUR] <sup>+</sup>             | 152.98 | 8.04   | 158    | 133    | 178    | 323   |
| Branch Network                         | 0.00   | 1.00   | -0.15  | -2.42  | 2.48   | 323   |
| Access by Phone                        | 0.00   | 1.00   | 0.28   | -2.95  | 1.39   | 323   |
| Alternative Medicine                   | 0.00   | 1.00   | -0.17  | -2.16  | 3.16   | 323   |
| Supplementary Benefits                 | 0.00   | 1.00   | 0.06   | -4.73  | 1.93   | 323   |

Notes: Authors' calculation based on the SOEP and sickness fund information provided by *Kassensuche GmbH*. <sup>+</sup> denotes fictive absolute EUR premiums based on a monthly gross income of 2,000€ for the sake of illustration. The reason is that the premium depends on three parts: the sickness fund contribution rate, the individual income, and the sickness fund add-on premium (after 2009). In order to show average Euro amounts on the sickness fund level, we use a hypothetical monthly gross income of 2,000€. In the regression models, exact premiums are calculated based on enrollee and sickness fund level information.

SOEP interviews are typically carried out in the first quarter of the year, while sickness fund characteristics were collected at the end of a calendar year in November and December. Thus we link the respondents' health plan choice sets at the time of the interview in the first months of a year with the health plan information as provided at the end of the prior calendar year. Hence, we make use of switching and health plan data for the years 2007 to 2010.

We use individual's wage earnings reported in the SOEP to calculate health plan premiums for all potential choices in Euro amounts at each point in time. In addition we make use of information on age, gender and self-reported health status (SAH) later in a subsection on heterogeneity by demographic groups. As shown in Panel B of Table 3.1, slightly more than half the sample is female and the average age is 37 years. Thirteen percent self-rate their health as 'very good' and 49% as 'good'.

### 3.4.2 Health Plan Level Data

Information on the health plan characteristics (contribution rate, optional benefits and service quality) is provided by a private company (*Kassensuche GmbH*). It is collected through questionnaires that are sent out annually to all active sickness funds. Sickness funds have a strong incentive to participate in the survey, as *Kassensuche GmbH* operates a large German web portal where consumers can compare

a broad range of characteristics of existing sickness funds. Moreover, at the end of each year, a popular weekly business magazine (*Focus Money*) publishes a detailed overview and ranking of the best 50 health plans as surveyed by *Kassensuche GmbH*. This health plan ranking is comprised of sub-scores for several subcategories, measured on continuous scales, which provide the basis for the benefit and service quality characteristics used in our regression model.<sup>15</sup> Since this is the same information that consumers obtain, directly exploiting this information is one main advantage of our approach. The main drawback of using this data is that interpretation of the computed scores is not straightforward as we discuss below. To account for slight differences in the calculation of the sub-scores over time, the regression models make use of the z-transformed sub-scores.<sup>16</sup> In total, we have information on 115 different sickness funds covering the years 2007 to 2010. The health plans included every year have a total market share of around 80% and also represent 80% of all existing plans (Müller and Lange, 2010).

**Price information** for each sickness fund is mainly based on pre-2008 publicly available health plan-specific contribution rates. Post-2008, we additionally take sickness fund specific add-on premiums and refunds into account (see section 3.2). We link this publicly available information to both, individuals' gross income and the federally fixed yearly contribution ceiling, in order to calculate the exact monthly health plan premiums (in euros) that each enrollee pays. We do not consider the employer share, which is legally fixed at 50% of the total premium.<sup>17</sup> We disregard the employers' share since employees typically believe that they solely pay the employee share as premium and are thus very likely to make decisions solely based on their share. As seen in Panel C of Table 3.1, the share of the monthly premium that individuals carry – based on average monthly gross earnings of 2,000 € – ranges between 133 € and 178 €, with a mean value of 153 €.

**Optional supplemental benefits** cover additional health care services that are not part of the standard SHI benefit package as defined by the federal regulator, such as immunizations for tropical diseases or preventive screenings for breast or skin cancer in younger ages. Moreover – in being more generous – sickness funds can deviate from the mandated minimum benefit package for domestic help and rooming-in. For example, federal legislation requires sickness funds to pay for domestic help for children aged 12 and younger with parents who are institutionalized for medical treatment (and no other household member or relative is available). More generous plans extend this coverage to children aged 14 and younger.

The optional supplemental benefits that sickness funds provide in addition to the federally mandated benefits (*Kassenleistungen*) enter the empirical model in terms of two variables (sub-scores): (i) *alternative medicine* and (ii) *supplemental benefits*. The score of *alternative medicine* is mainly based on the number of different alternative medical treatments offered by each sickness fund. Sickness funds are not entirely free to offer any additional treatment, but may choose from a list of around 20 approved treatments (e.g. ayurveda or homeopathy). Additionally, the score takes into account whether these treatments are restricted to certain regions or physicians. More restrictions lead, *ceteris paribus*, to a

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<sup>15</sup>The number of subcategories has slightly changed over time, therefore we use only those scores which were part of the survey in each of the four years.

<sup>16</sup>The z-transformation is conducted for each year separately.

<sup>17</sup>Effective July 1, 2005, the strict equal sharing of contributions was altered. Between 2005 and 2015, the employees' share was  $[0.9 + 0.5 \times (cr - 0.9)]$  percent of their gross wage up to the contribution ceiling, where  $cr$  denotes the overall contribution rate. In the example above, this amounts to an employee share of 7.45 percent and an employer share of 6.55 percent of the gross wage. If the incidence of the full health insurance contribution was fully on employees, this would simply reduce the price coefficients.

lower score. Panel C of Table 3.1 provides some key descriptive statistics on *alternative medicine* and the other scores. While the *z*-transformation renders the mean uninformative, the negative median value indicates that the distribution of *alternative medicine* is skewed to the right.

**Health plan service quality** is measured by two variables: (i) *branch network* and (ii) *accessibility by phone*. The score of *branch network* measures the density of the branch network and takes into account that roughly half of all sickness funds are only active in certain federal states and, hence, are likely to have fewer branches than those who operate nationwide. More precisely, the original score before the *z*-transformation is derived from the log of the total number of branches divided by the number of federal states in which the sickness fund operates. *Accessibility by phone* considers the different types of available hotlines (medical, non-medical) and how many hours these hotlines are staffed. Differences in staff quality – i.e., the share of staff with special qualifications, such as social insurance clerks (*“Sozialversicherungsfachangestellte”*), physicians, nurses or pharmacist – are accounted for by weighting the hotline’s operating hours accordingly, where higher staff quality receives a higher weight.

The joint distribution of health plan characteristics exhibits positive correlations between all considered variables, ranging from 0.102 (‘supplemental benefits’ and ‘branch network’) to 0.549 (‘alternative medicine’ and ‘access by phone’). This indicates that sickness funds seem to position themselves either at the high or low benefit and service plan end in the market, rather than trying to build a specific reputation by offering very specific extra benefits or boosting specific quality indicators. This corresponds with the observation that the scores for service quality and additional benefits are positively correlated with prices; the correlations range from 0.053 (supplemental benefits) to 0.228 (branch network). Hence high benefit and service plans are on average the more expensive plans.

The positive correlation of premiums and service quality/extra benefits seems to indicate that sickness funds are aware of the quality-price trade off when they differentiate their product. Another interesting descriptive result highlights the relevance of health plan literacy: Considering the five plan characteristics above, the majority of plans in the market are dominated by at least one competitor. That is, there is at least one competitor that is better in all five characteristics. This holds for every single year with the shares of dominated plans ranging from 0.67 (2008) to 0.90 (2010).

## 3.5 Results

### 3.5.1 Descriptives

To obtain a first impression of whether prices, optional benefits, or service quality matter in an individual’s decision to choose a health plan, we compare means of sickness fund characteristics of new and old plans for switchers. The results are based on 729 switches with information on both, the new and the old health plan.<sup>18</sup> As can be seen in Table 3.2, average health insurance premiums are lower for the new health plan chosen as compared to the old health plan. The average difference is 3.56 € per month, indicating that price is a relevant determinant in health plan choice. For service quality characteristics, we do not observe significant differences between the new and the old health plans. The same applies

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<sup>18</sup>Note that for the main analysis we only need information on the new health plan which is available for more individuals.

Table 3.2: New and Old Health Plan Characteristics for Switchers

| Characteristic         | $\bar{X}^{new}$ | $\bar{X}^{old}$ | $\Delta$ | $s.e._{\Delta}$ |
|------------------------|-----------------|-----------------|----------|-----------------|
| Premium                | 162.47          | 166.04          | -3.56*** | (0.30)          |
| Branch Network         | 0.91            | 0.88            | 0.04     | (0.05)          |
| Access by Phone        | 0.75            | 0.77            | -0.02    | (0.03)          |
| Alternative Medicine   | 0.88            | 0.85            | 0.03     | (0.05)          |
| Supplementary Benefits | 0.37            | 0.34            | 0.03     | (0.04)          |

Notes: Authors' calculation. The table shows means of sickness fund characteristics for new and old health plans. The calculations are based on 729 observations. Standard errors of the differences in means are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

to supplemental benefits, where we find no significant differences either for alternative medicine or for optional benefits. The quality differences between old and new plans are very small and below 0.05. Overall, the descriptive results provide first evidence that premium differences may have an effect on switching behavior while optional benefits and service quality seem to play a minor role in health plan choice.

### 3.5.2 Main Results from Mixed Logit Models

Table 3.3 shows two different specifications of the model outlined in section 3.3. It reports the estimated means and standard deviations of the random coefficients. Model 1 solely includes health plan premiums, optional benefits, and service quality, while Model 2 adds a set of sickness fund fixed effects.

According to Model 1, individuals prefer sickness funds with lower insurance premiums, as indicated by the significantly negative mean coefficient of *premium*. The corresponding estimated standard deviation is close to zero and not significant, suggesting that the relationship between premiums and individual sickness fund choice is largely homogeneous across individuals.

With respect to service quality, we observe significantly positive mean coefficients for both, *branch network* and *accessibility by phone*. In addition, the estimated standard deviations point towards considerable heterogeneity. Considering health plan benefits, the results suggest that alternative medical treatments are not significantly associated with insurance choice. Both the estimated mean and the standard deviation are close to zero and not significantly different from zero. In contrast, the estimated mean parameter of *supplemental benefits* exhibits the expected positive sign and is highly significant. Since our models impose that the coefficients follow a normal distribution, we can use the estimated mean and standard deviation to calculate the share of individuals that place a positive value on optional supplemental benefits (Train, 2009). The corresponding probability is given by  $P(X > 0) = 1 - F_X(0) = 1 - \Phi(0 - 0.433/0.755) \approx 0.717$ , where  $\Phi$  represents the cumulative distribution function of the standard normal distribution. The calculation would suggest that, according to Model 1, around 70% of all enrollees place a positive value on optional supplemental benefits.

It is likely, however, that the variables on the sickness fund level capture other unobserved health plan characteristics, such as brand loyalty, awareness, or the general reputation of the fund. Therefore, Model 2 adds a full set of sickness fund fixed effects. As for the impact of *premium*, the estimated mean coefficient and standard deviation are close to what we find in Model 1 suggesting a minor role of unobserved confounding factors. Although slightly smaller in absolute magnitude, the estimated

Table 3.3: Main Estimation Results - The Role of Price, Non-Essential Benefits, and Service Quality in the Health Plan Choice Decision

|                        | Model 1           |                  | Model 2           |                  |
|------------------------|-------------------|------------------|-------------------|------------------|
|                        | Mean              | SD               | Mean              | SD               |
| Price                  |                   |                  |                   |                  |
| Premium                | -0.092*** (0.006) | 0.003 (0.016)    | -0.061*** (0.008) | 0.002 (0.014)    |
| Service Quality        |                   |                  |                   |                  |
| Branch Network         | 1.600*** (0.052)  | 0.774*** (0.065) | 0.063 (0.110)     | 0.354*** (0.128) |
| Access by Phone        | 0.964*** (0.108)  | 0.618*** (0.119) | 0.052 (0.152)     | 0.210 (0.335)    |
| Benefits               |                   |                  |                   |                  |
| Alternative Medicine   | -0.044 (0.041)    | 0.039 (0.135)    | 0.069 (0.071)     | 0.371*** (0.108) |
| Supplementary Benefits | 0.433*** (0.055)  | 0.755*** (0.071) | 0.058 (0.064)     | 0.182 (0.150)    |
| SF Specific Constants  |                   |                  |                   | ✓                |
| # Observations         | 99,888            |                  | 99,888            |                  |
| # Choice Occasions     | 1,726             |                  | 1,726             |                  |

Notes: Authors' calculation. The table shows estimated coefficients of both, mean and standard deviation of the random parameters. Estimated standard errors are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

mean coefficient exhibits the expected negative sign and remains highly significant. As in Model 1, the estimated standard deviation is virtually zero, indicating a homogeneous relationship between premiums and health plan choice across individuals. Virtually everyone in the sample places a negative value on higher prices.

In contrast, when considering time-invariant health plan level effects, all mean coefficients of service quality and optional benefits dramatically shrink in size and become insignificant. In absolute terms, the magnitudes of these coefficients fall within the same range as the estimated *premium* coefficient. However, not only are the standard errors much larger, the variables are also measured on different scales, which needs to be taken into account when interpreting the results. Comparing the effect of an increase by one standard deviation – which is about eight for the premium and one for the other variables (cf. Table 3.1, Panel C) – the response to a price increase is eightfold the response to an increase in service quality or optional benefits. Thus, we conclude that including health plan fixed effects is essential here, and that this is our preferred specification.

Next, while the standard deviations of the coefficients for *accessibility by phone* and *supplemental benefits* are small and insignificant, those of *branch network* and *alternative medicine* suggest significant heterogeneity in preferences for these factors. Around 40 to 60% of all enrollees either place a positive or negative value on these health plan characteristics (using the formula above). While some individuals seem to prefer more benefits and a better service, others actually want less. Individuals who do not need or want to physically visit their sickness fund branches may think that a large *branch network* would be a waste of money. Moreover, given that the usefulness of alternative medicines is not proven, the same argument may hold for *alternative medicine*.

Overall, the estimation results are in line with the simple descriptive results and intuition. They suggest that differences in health plan premiums are the main determinant in sickness fund choice. Medically non-necessary supplemental health plan benefits and service quality play, on average, a negligible role in consumers' health plan choice decisions. One explanation for this finding would be that quantitative premium differences are easy to understand and process for most people. The monetary trade-off to



service quality parameters is much more abstract and may only become apparent when customers actually need help (Schram and Sonnemans, 2011). Research on Medicare Part D has also demonstrated that the insured do not always enroll in the optimal health plan and that they learn to improve their selection over time (Heiss et al., 2006, 2013; Abaluck and Gruber, 2011; Ketcham et al., 2012). Another explanation for our finding may be a low awareness of health plan differences in terms of service quality and optional benefits.

### 3.5.3 Quantifying the Tradeoff between Prices, Service Quality, and Optional Benefits

We now have a closer look on the relative importance of the different health plan characteristics for consumer health plan choice. We can exploit this information in any discrete choice model – which is based on a linear index as in equation (3.1) – the ratios of the coefficients represent marginal rates of substitution (*MRS*).<sup>19</sup> We focus on how consumers value health plan differences in supplemental benefits and service quality, compared to premium differences. More specifically, we are interested in  $-\delta_i^k/\gamma_i$  and  $-\zeta_i^k/\gamma_i$  that indicate at which rate enrollee  $i$  is willing to trade-off additional benefits or better quality against a premium decrease, where  $k$  indexes benefit and quality characteristics. In other words, if sickness fund  $j$  increases the premium by one unit, the probability the plan being chosen by enrollee  $i$  does not change if, at the same time, its phone accessibility improves by  $-\zeta_i^{access}/\gamma_i$  units. Interpreting these ratios, however, requires scales that measure a one unit change. As no natural scale is available for optional benefits and service quality, we define a unit as one standard deviation of the relevant characteristic in the sample distribution. Similarly, we define one premium unit. Yet, unlike for the service and quality measures, an increase in the monthly premium by one standard deviation can also be expressed as an absolute 8€ increase (cf. Table 3.1, Panel C). This value has some intuitive appeal, as it represents the typical premium differential between health plans after 2008. For health plans that increased prices, 8€ is also close to the average price increase in 2007 and 2008 (Schmitz and Ziebarth, 2011).

Mixed-logit estimation does not yield estimates for  $-\delta_i^k/\gamma_i$  and  $-\zeta_i^k/\gamma_i$  at the individual level and, for this reason, does not allow for the calculation of individual marginal rates of substitution. What one obtains from the estimation are normally distributed population parameter estimates  $\mu_k$  and  $\sigma_k$ . As  $MRS_k$  is a ratio of normal random variables, its distribution involves a Cauchy-component rendering the mean (and higher-order moments) undefined which cannot consistently be estimated (cf. Marsaglia, 1965; Cohen Freue, 2007). Hence, we have to base the discussion on quantiles rather than the mean of  $MRS_k$ . In particular, we focus on the median of  $MRS_k$ . Rather than directly interpreting  $-\hat{\mu}_k/\hat{\mu}_{premium}$  as *ML*-estimate for the median of  $MRS_k$ , we simulate the percentiles of the *MRS*-distributions – along with corresponding 95%-confidence bands – on basis of the results for Model 2 (cf. Table 3.3, right panel).<sup>20</sup>

<sup>19</sup>One may just as well refer to this ratio as ‘rate of substitution’ since it does not change due to linearity.

<sup>20</sup>The reason is that the ratio of the means  $\mu_k/\mu_i$  does not provide an accurate approximation of the median of the corresponding ratio distribution – if the denominator distribution has a mean close to zero and a non-vanishing density at zero. To estimate the percentiles, we draw 2 million random numbers from the relevant ratio distributions, with the point estimates  $\hat{\mu}_k$ ,  $\hat{\mu}_{premium}$ ,  $\hat{\sigma}_k$ , and  $\hat{\sigma}_{premium}$  entering the involved normal distributions, and then average the simulated quantiles over 2,000 replications. Due to the large size of the pseudo sample, the estimated percentiles exhibit very little sampling variability and averaging has almost no effect. To simulate the confidence bands, we also sample 2,000 times where, in each replication, the four relevant parameters are drawn from the (estimated) jointly-normal distribution of the *ML*-estimator.

### The Density of the Branch Network vs. a Lower Premium

Let us start with  $MRS_{branch}$ . The simulated median of  $MRS_{branch}$  is 0.128, indicating that the median enrollee trades-off lower premiums against a higher density network of branches at a rather small rate. More precisely, an increase in the branch network by one standard deviation (S.D.) is just valued as one-eighth S.D. of the premium, which translates to 1 € per month. However, the simulated 95%-confidence interval of  $[-0.324, 0.564]$  indicates that this value is imprecisely estimated.<sup>21</sup> Nevertheless, even the upper confidence bound is only 0.56 and lets us exclude – with 95% statistical certainty – that consumers would trade an increase in the branch density network by one S.D. for more than 8.50 € per month.

This picture somewhat changes when we consider the estimated heterogeneity in the  $MRS$ . Although the exact shape of the estimated  $MRS$  distribution depends heavily on distributional assumptions (and should be interpreted with caution), assessing other quantiles may provide insights in the variation of enrollees preferences. At the 95<sup>th</sup> percentile, the rate of substitution is more than ten times larger than at the median (point estimate 1.307). This means that, according to our estimates, those five percent of enrollees who have the strongest preferences for face-to-face services and a high branch density are willing to accept a 1.3 S.D. increase in the monthly premium (10 €) for a one S.D. increase in the branch density. However, this number carries a lot of uncertainty (confidence interval:  $[0.286, 3.064]$ ). On the other hand, according to the estimated distribution of  $MRS_{branch}$ , 42% of enrollees would not be willing to accept any increase in premium in exchange for more physical branches. Taking sampling error into account, one cannot even reject a number as high as 77% with 0.95% certainty. All in all, a large fraction of German enrollees find a sickness fund's branch network as playing a marginal – if any – role in the health plan choice when compared to the premium. Yet, due to large heterogeneity, a small fraction of enrollees seem to value personal customer-to-customer services a great deal.

### Telephone Access and Supplemental Benefits vs. a Lower Premium

Turning to the remaining optional benefit and service characteristics, the pattern of estimated  $MRS$ s is similar to what we found and discussed for 'branch network' above. The estimated median  $MRS$ s range from  $1/7$  to  $1/10$  (access by phone: 0.106; alternative medicine: 0.140; supplemental benefits: 0.118), indicating a rather low median willingness to pay for optional supplemental benefits like immunization shots, alternative medicine, and service quality. The point estimates, however, are accompanied by rather wide confidence intervals. At the 95<sup>th</sup> percentile, however, the estimated  $MRS$ s (access by phone: 0.808; alternative medicine: 1.379; supplemental benefits: 0.723) are 6 to 10 times larger than the median. About 40% of all enrollees are not willing to accept any premium increase in return for more optional benefits or a better service.

When individuals decide to enroll in a health plan, its premium will be compared to *all* of the services and benefits offered, which has not been considered by the discussion above that focused one single services and benefits. Thus we finally analyze how consumers would trade-off a simultaneous increase

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<sup>21</sup>Using  $-\hat{\beta}_{branch}/\hat{\beta}_{premium}$  directly as estimate for  $med(MRS_{branch})$  and applying the delta-method for calculating confidence intervals yields results (point estimate: 0.128, confidence interval:  $[-0.306, 0.561]$ ) that just marginally deviate from the simulation-based counterpart. This can be explained by the small value of  $\hat{\sigma}_{premium}$  that lets the density of the denominator almost vanish at zero.

by one S.D. for all four characteristics. That is, we consider  $-(\delta_i^{\text{branch}} + \delta_i^{\text{access}} + \zeta_i^{\text{alt. med.}} + \zeta_i^{\text{sup. benefits}}) / \gamma_i$ , for which we obtain estimates as for any  $MRS_k$  above. This calculation reflects an estimated median value of 0.491 (confidence interval:  $[-0.181, 1.181]$ ). Although – not surprisingly – the median willingness to pay for joint improvements in quality and benefits exceeds the median willingness to pay for single improvements, the value of the point estimate is still less than one. Like the  $MRS$ s for particular quality characteristics, the joint rate of substitution exhibits considerable heterogeneity. At the 95<sup>th</sup> percentile, the rate is 2.438, i.e., five times larger than at the median. However, considering the other tail of the distribution, 33% of the insured are not willing to accept any premium increase even if all considered services and benefits would simultaneously improve by one unit.

### 3.5.4 Heterogeneity Analysis

#### The Reform of 2009

As mentioned in section 3.2, our sample period covers a price setting reform that became effective in January 2009. Prior to 2009, price differences between sickness funds were expressed in contribution rate differences. After 2009, contribution rates were fixed across all funds. Furthermore, price differences between health plans were expressed as flat euro add-on premium or refund. Schmitz and Ziebarth (2011) and Wuppermann et al. (2014) find substantial effects of this reform on health plan switching behavior.

*A-priori*, it is unclear whether differences in non-essential benefits and service quality became more or less salient after this price framing reform. On the one hand, because health price differences became more salient post reform, price differences could have increased in importance relative to other plan characteristics. On the other hand, because the market price dispersion decreased after 2009, a decrease in price variation across funds could have made quality differences more relevant to consumers.

To test whether the impact of prices, optional supplemental benefits, and service quality structurally changed post-reform, we split our sample into a pre- (2008/2009) and post-reform (2010/2011) period.<sup>22</sup> As can be seen in Table 3.4, the estimated mean coefficient of *premium* is about twice as large post-reform, which is in line with Schmitz and Ziebarth (2011) and Wuppermann et al. (2014). The estimated coefficients for *alternative medicine* and *supplemental benefits* are almost identical in pre and post reform years. All in all, it seems to be justified to not distinguish by the pre- and post-reform time periods in the main specification. This conclusion is also supported by an LR-test that fails ( $p$ -value 0.599) to reject the null hypothesis of equal distributions.

#### Health and the Potential for Cream Skimming

The German social health insurance system combines guaranteed issue with income-dependent contribution rates. Individual risk rating is strictly prohibited. This regulation, however, creates an incentive for sickness funds to engage in active or passive health risk selection. To minimize this incentive, a comprehensive risk adjustment scheme exists. The scheme is based on age, gender, a reduced earnings capacity, and 80 chronic illnesses, such as diabetes or cancer. However, because the risk adjustment

<sup>22</sup>We opt for assigning the wave 2009 to the pre-reform period, as SOEP interviews are typically carried out at the beginning of a year and, hence, switching most likely refers to the previous year.

Table 3.4: Heterogeneity I - Reform 2009

|                             | Mean              | SD               |
|-----------------------------|-------------------|------------------|
| Price                       |                   |                  |
| Premium × pre               | −0.056*** (0.009) | 0.001 (0.014)    |
| Premium × post              | −0.092*** (0.031) | 0.069 (0.042)    |
| Service Quality             |                   |                  |
| Branch Network × pre        | −0.010 (0.119)    | 0.276 (0.200)    |
| Branch Network × post       | 0.203 (0.139)     | 0.475*** (0.167) |
| Access by Phone × pre       | 0.152 (0.189)     | 0.428* (0.223)   |
| Access by Phone × post      | −0.008 (0.171)    | 0.125 (0.341)    |
| Benefits                    |                   |                  |
| Alternative Medicine × pre  | 0.073 (0.115)     | 0.260 (0.168)    |
| Alternative Medicine × post | 0.093 (0.107)     | 0.651*** (0.177) |
| Supp. Benefits × pre        | 0.010 (0.068)     | 0.012 (0.180)    |
| Supp. Benefits × post       | 0.076 (0.102)     | 0.136 (0.167)    |
| SF Specific Constants       |                   | ✓                |
| # Observations              |                   | 99,888           |
| # Choice Occasions          |                   | 1,726            |

Notes: Authors' calculation. The table shows estimated coefficients of both, mean and standard deviation. The binary indicator "pre" is one for the SOEP waves 2008 and 2009, while "post" is one for the waves of 2010 and 2011. Estimated standard errors are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

scheme does not perfectly adjust for health risks, allocated revenues for high risk enrollees may still be smaller than actual costs. Still, it is unclear to what extent risk selection exists in the German market. While Bauhoff (2012) finds some evidence for direct risk selection based on the state of residence of the insured – which is found to be very small, however, in quantitative terms – Nuscheler and Knaus (2005) find no indication for risk selection in the German SHI.

Sickness fund diversity is important for sufficient competition in the market. If health plans are not allowed to diversify their products at all, enrollees will not have the ability or an incentive to search for and switch to the best health plans in the market. On the other hand, such diversity could also be exploited for indirect risk selection. For example, there is the notion that better educated individuals are more likely to choose health plans that include alternative medicine. Offering alternative medicine could therefore be a mechanism for sickness funds to attract lower risks.

This paper cannot directly test whether cream skimming exists in the German SHI. However, we indirectly assess the *potential* for indirect risk selection by analyzing heterogeneous responses to differences in prices, service quality and optional benefits. Risk selection strategies could be employed if healthy and unhealthy individuals were attracted differently by different health plan characteristics.

To classify individuals into different risk types, we use the self-assessed health (SAH) measure, age, and gender. Even though the German risk-adjustment is based on health, age, and sex, we argue that this simplistic approach is useful for several reasons. First, SAH is a more comprehensive measure and includes more information than the 80 illnesses considered in the risk equalization scheme. Second, SAH also includes more up-to-date information as enrollees' illnesses of the previous year enter the risk adjustment formula, but not current ones. Third, despite its simplicity, SAH has been shown to be an excellent predictor of true health (McGee et al., 1999). Issues related to reporting heterogeneity seem to be mostly limited to age and gender (Ziebarth, 2010b). Fourth, even though age and sex are included

Table 3.5: Heterogeneity II - Risk Types

|                             | Age<br>(G <sup>1</sup> : age < 50) |                  | Gender<br>(G <sup>1</sup> : males) |                 | SAH<br>(G <sup>1</sup> : SAH < 3) |                  |
|-----------------------------|------------------------------------|------------------|------------------------------------|-----------------|-----------------------------------|------------------|
|                             | Mean                               | SD               | Mean                               | SD              | Mean                              | SD               |
| Price                       |                                    |                  |                                    |                 |                                   |                  |
| Premium × G <sup>1</sup>    | -0.063*** (0.009)                  | 0.001 (0.015)    | -0.054*** (0.010)                  | 0.015 (0.028)   | -0.059*** (0.009)                 | 0.005 (0.020)    |
| Premium × G <sup>2</sup>    | -0.053*** (0.013)                  | 0.000 (0.028)    | -0.070*** (0.010)                  | 0.004 (0.015)   | -0.069*** (0.011)                 | 0.002 (0.022)    |
| Service Quality             |                                    |                  |                                    |                 |                                   |                  |
| Branches × G <sup>1</sup>   | 0.056 (0.112)                      | 0.350** (0.145)  | 0.083 (0.122)                      | 0.317* (0.177)  | 0.041 (0.119)                     | 0.302* (0.183)   |
| Branches × G <sup>2</sup>   | 0.004 (0.134)                      | 0.154 (0.398)    | -0.008 (0.112)                     | 0.264 (0.192)   | 0.054 (0.124)                     | 0.422*** (0.147) |
| Phone × G <sup>1</sup>      | 0.187 (0.154)                      | 0.442*** (0.158) | 0.128 (0.167)                      | 0.384** (0.178) | 0.307* (0.166)                    | 0.560** (0.155)  |
| Phone × G <sup>2</sup>      | -0.069 (0.172)                     | 0.153 (0.277)    | 0.236 (0.174)                      | 0.519** (0.172) | -0.098 (0.149)                    | 0.114 (0.329)    |
| Benefits                    |                                    |                  |                                    |                 |                                   |                  |
| Alt. Med. × G <sup>1</sup>  | 0.064 (0.074)                      | 0.325*** (0.123) | 0.058 (0.087)                      | 0.523** (0.105) | 0.023 (0.080)                     | 0.499** (0.112)  |
| Alt. Med. × G <sup>2</sup>  | 0.021 (0.114)                      | 0.272 (0.262)    | 0.064 (0.074)                      | 0.030 (0.219)   | 0.170* (0.090)                    | 0.164 (0.222)    |
| Supp. Ben. × G <sup>1</sup> | 0.060 (0.065)                      | 0.143 (0.158)    | 0.121 (0.077)                      | 0.178 (0.156)   | 0.083 (0.069)                     | 0.150 (0.142)    |
| Supp. Ben. × G <sup>2</sup> | 0.072 (0.114)                      | 0.357** (0.216)  | 0.042 (0.077)                      | 0.319** (0.141) | 0.058 (0.089)                     | 0.375** (0.168)  |
| SF Specific Constant        |                                    | ✓                |                                    | ✓               |                                   | ✓                |
| # Observations              | 99,888                             |                  | 99,888                             |                 | 99,790                            |                  |
| # Choice Occasions          | 1,726                              |                  | 1,726                              |                 | 1,724                             |                  |

Notes: Authors' calculation. The table shows estimated coefficients of both, the mean and the standard deviation of the random parameters. G<sup>1</sup> and G<sup>2</sup> denote good health risks (age < 50; males, SAH < 3) and bad health risks (age ≥ 50; females, SAH ≥ 3), respectively. Estimated standard errors are in parentheses. \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1. Significant differences between the distributions of estimated preference parameters are highlighted in gray.

in the risk-adjustment formula, these indicators are not perfect risk adjusters. We stratify the results based on these easy-to-observe socio-demographics since they likely carry other correlated important health information. Also, gender and age can be easily observed and then considered by insurers for active or passive risk selection.

We cannot include the variables in the most flexible way for computational reasons. Estimation time and tractability of the model and stability of the estimation results are the main factors behind this restriction. Therefore, for each of the variables, we construct a mutually exclusive subset of two dichotomous indicators G<sup>1</sup> (group 1) and G<sup>2</sup> (group 2) that represent different health risks. SAH is reported on a five point scale, ranging from 1 (very good) to 5 (bad). We require “good health risks” to report at least good health (SAH category 1 or 2), while bad health risks fall into categories 3 to 5. Age is collapsed into two binary variables marking individuals aged younger than 50 (G<sup>1</sup>) and older than 50 (G<sup>2</sup>). We also use separate indicators for males (G<sup>1</sup>) and females (G<sup>2</sup>); females use more health care and have higher expenditures.

We run one regression for each of the three separating variables and interact health plan characteristics with the corresponding indicators for both groups. As we have imposed a normal distribution for the random coefficients, conducting a joint test on equal coefficients (mean and S.D.) allows us to test whether the distributions of preferences differ significantly between high and low risks. This is essentially the approach adopted by Beaulieu (2002) and Wang et al. (2011), who run conditional logit and mixed logit models on different subsamples and compare the distributions of the estimated parameters across subsamples. Recall that we cannot include baseline levels of socio-economic controls that do not vary over the choice sets for each enrollees (see section 3.3).

Table 3.5 presents the results of the heterogeneity analysis with respect to age, gender, and SAH. Significant differences between the distributions of the preference parameters are highlighted in gray. First,

we compare the share of enrollees who place a positive value on certain health plan characteristics. Using age as a separating variable, we find no significant differences between the distributions of taste parameters.

With respect to health plan premium, the estimated distributional parameters are close to what we observe in the main specification without interaction terms (cf. Model 2 in Table 3.3). No differences are found when we stratify by age, gender, or health status. This means that the sick and the healthy, the young and the old, as well as males and females all value health plan prices in a similar fashion. The same holds for the factor *branch network*.

With respect to *accessibility by phone*, the null hypothesis is rejected when we stratify by gender and health status ( $p$ -values: 0.0059/0.0179). While the estimated shares of enrollees who value a good hotline service is almost equal in the gender specification ( $G^1$ : 63%,  $G^2$ : 67%), the difference seems to be substantial in the SAH specification ( $G^1$  (good health): 71%,  $G^2$  (bad health): 19%). This indicates that good health risks value good phone accessibility *more* than bad health risks.

The opposite holds for *alternative medicine*. Again, the hypothesis of equal distributions for gender and health is rejected ( $p$ -values: 0.0823 / 0.0309), but the share of those who value these treatments is much larger among bad health risks in both specifications (SAH:  $G^1$ : 52%,  $G^2$ : 85%; also gender:  $G^1$  (men): 54%,  $G^2$  (women): 98%).

Finally, with respect to *supplemental benefits*, the null hypothesis of equal distributions is likewise rejected for gender and health ( $p$ -values: 0.0823 / 0.0309), indicating that those in good health value supplemental benefits more than bad health risks (SAH:  $G^1$ : 71%,  $G^2$ : 56%; also gender:  $G^1$  (men): 75%,  $G^2$  (women): 55%).

In total, preference differences between age, gender and health status are rather small. When they exist, they do not point into one clear direction. Thus, we conclude that – in the current German public health insurance – supplemental benefits and services do not seem to be powerful tools for indirect cherry picking because different risk types do not seem to systematically react to special health plan features.

### 3.6 Conclusion

This paper exploits a unique institutional setting and linked individual and health plan level data to assess the relative roles of prices, non-essential benefits, and service quality in the decision to choose health plans. Individuals' health plan choices are modeled using a random parameters model which accounts for health plan heterogeneity and time-invariant unobserved factors. In total, the empirical setting exploits 1,724 health plan choices and almost 100,000 potential choice sets between 2007 and 2010.

We find that prices play the dominant role in the decision to choose health plans and only see limited effects of the provision of non-essential benefits and service quality. In quantitative terms, for the median enrollee, a one S.D. increase in any of the non-price factors evaluated (density of branches, telephone access, alternative medicine, and other optional supplemental benefits) is offset by a one-eighth S.D. decrease in premiums, or 1 € per month. In other words, even when service quality and

non-essential benefits play a role in the decision to choose health plans, enrollees are willing to trade them against lower premiums at a rather small rate. However, we find that up to 70% of all enrollees do not value these non-price attributes at all. On the other hand, we find that heterogeneity in consumer valuation of non-price health plan attributes is very large and a minority of enrollees may value service quality a great deal.

These findings hold in an institutional setting where differences in service quality and optional benefits should, in principle, be more salient than in other markets – due to a heavy federal regulation including standardization of the benefit package and cost-sharing parameters. Yet, the minor relevance of service quality and additional benefits could also be a result of heavy federal regulations and standardized benefits. On the other hand, online portals – that cover the entire German market and provide information on standardized non-price attributes – facilitates the comparison and switching of plans. Our empirical approach is based on exactly this standardized supply-side information that consumers use to make their health plan choice.

According to standard economic theory, absent adverse and risk selection, allowing health plans to diversify more would unambiguously increase consumer choice and welfare. Our empirical findings, which suggest heterogeneity in consumer valuation of non-price attributes underscores this notion. However, recent research in behavioral economics has challenged the rationality assumption and provides evidence for phenomena such as decision overload, an occurrence that stems from complex multidimensional choice sets. With regard to Germany's heavily regulated market, allowing insurers to diversify their product to a greater extent could imply (i) selective contracting and the formation of provider networks, (iii) more leeway to vary cost-sharing amounts, or (ii) more leeway to exclude benefits from the very generous federally mandated benefit package.

As in every empirical study, the strict interpretation of our results is limited to the specific setting, in our case the German market. However, we believe that the findings are of broader relevance, particularly since ours is one of the first studies exploiting and disentangling the role of the two factors “non-essential benefits” and “service quality” relative to prices. One promising opportunity for future research could address the ability of consumers to cognitively process the information provided to them and transmit the information into behavioral action.

## Chapter 4

# Does New Health Information Affect Health Behavior? The Effect of Health Events on Smoking Cessation

### 4.1 Introduction

In the fight against smoking prevalence, public health policymakers usually pursue three objectives: *(i)* protecting non-smokers from second-hand smoke, *(ii)* preventing non-smokers from taking up smoking and *(iii)* motivating current smokers to quit. To address these objectives, various tobacco control policies are available, which can be categorized into three groups: *(i)* tobacco taxation, *(ii)* smoking bans and *(iii)* information campaigns about the health consequences of smoking. This paper focuses on the effect of new health information on behavioral change. To be more concrete, the study investigates the relationship between different kinds of health problems, which serve as proxies for health information, and the decision to quit smoking. Whether and how such information affects health behavior is of general interest for public health policymakers, as the use of information campaigns is not restricted to smoking but also applies to other fields of substance abuse. In the context of smoking prevalence this is an important question as anti-smoking campaigns that primarily rely on providing information on the detrimental health consequences of smoking can be considered as effective only if individuals respond to this information. That is, such information needs to induce behavioral change among smokers in terms of smoking cessation or at least reducing consumption levels.

Existing empirical evidence with respect to the effect of health information on smoking behavior, in particular on smoking cessation, is mixed. One strand of the literature directly investigates the effects of several types of information campaigns on smoking prevalence. Liu and Tan (2009) observe that anti-smoking media campaigns significantly decreased the prevalence of smoking in California. In a controlled trial, McVey and Stapelton (2000) observe a reduction in smoking prevalence as a consequence of anti-smoking television campaigns in England. Using regional variation of per capita

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See Bünnings (2013) for an earlier working paper version of this chapter.



tobacco control expenditures in Switzerland, Marti (2013) estimates a discrete time hazard model and finds a positive effect of tobacco control expenditures on the probability of quitting smoking. Bardsley and Olekalns (1999), however, find both health warnings on cigarette packs and workplace bans to have only minor effects on tobacco consumption in Australia.

Analyzing the effects of anti-smoking campaigns on smoking behavior usually raises the issue of how to measure exposure to and perception of such information. To circumvent this problem, a second strand of the literature exploits the experience of a health problem as specific type of health information (Clark and Etilé, 2002; Sundmacher, 2012; Hsieh, 1998). The latter two interpret a drop in self-assessed health as the occurrence of a health event and observe a positive effect of worsened health on the probability to quit smoking. Although self-assessed health has been shown to be a good predictor for both morbidity and mortality (Idler and Benyamini, 1997), it does not allow to identify what causes the health event. However, different health events may induce different reactions in terms of health behavior. Exploiting panel data from the Health and Retirement Study, Smith et al. (2001) observe that smokers downgrade their longevity expectations after a smoking-related health event more dramatically than after experiencing general health problems. Using data from the British Household Panel Survey, Clark and Etilé (2002) analyze the effect of self-perceived changes in overall health as well as more smoking related health diseases, such as heart and lung check-ups. Except for the latter category, they observe a higher likelihood to quit smoking among those who experienced such a health problem. In contrast, Lasser et al. (2000) and Ziedonis et al. (2008) find that individuals who suffer from mental disorders have significantly lower quitting rates than smokers without mental health problems.

This paper is closely related to the second strand of the literature and contributes to the understanding of how new health information in terms of health problems affects individual's inclination to stop smoking. Using longitudinal individual-level data from the Swiss Household Panel, this paper tests whether (i) health problems motivate smokers to stop smoking at all and (ii) different types of health events (physical health problems, mental disorders, accidents) may induce different reactions among smokers. The decision to quit smoking is modeled in the fashion of a discrete time hazard model with smoking cessation as the absorbing state. To account for the presence of an almost quasi-separation problem with respect to one of the key explanatory variables (mental problems), a modified likelihood function is maximized. In line with previous studies, the empirical results suggest that individuals basically respond to health events. Exploiting more detailed information on the type of health event reveals that the positive overall effect is mainly driven by health problems due to physical reasons. Although I also observe a substantial negative relationship between mental health problems and the probability of smoking cessation, this result is statistically not significant. Accidents, in turn, have virtually no effect on smoking cessation. These results remain robust to a battery of additional robustness checks and suggest that providing information on the dramatic physical health consequences of tobacco consumption might be an effective tool to reduce smoking prevalence.

The remainder of the paper is organized as follows: The data set used for estimation is introduced in section 4.2. Section 4.3 outlines the empirical model and section 4.4 provides the estimation results along with the results obtained from several robustness checks. Concluding remarks are given in section 4.5.

## 4.2 Data

The empirical analysis is based on individual-level panel data from the Swiss Household Panel (SHP).<sup>1</sup> The SHP is a representative longitudinal survey in Switzerland, which started in 1999 and collects annual information from all household members aged 14 and older of more than 5,000 households. Along with a wide range of socioeconomic characteristics, the SHP provides information on a broad range of health related topics, such as mental and physical health as well as health behavior (Voorpostel et al., 2012). This paper uses the waves from 2000 to 2011.<sup>2</sup>

### 4.2.1 Smoking Histories and Dependent Variable

In 2010, a questionnaire module referring to individual's smoking behavior was introduced into the SHP. These questions cover current and past smoking behavior. More precisely, individuals state whether they currently smoke (*"Do you currently smoke?"*) and report their age at smoking onset (*"At what age did you start smoking regularly?"*) as well as their age at smoking cessation (*"At what age did you last smoke regularly?"*). Linking this information to individual's age at the time of their interviews, I am able to classify retrospectively whether an individual was a smoker/non-smoker at these points in time. An individual is defined as smoker if their age at the time of the interview is greater than or equal to the age of smoking onset and lower than the age at cessation. Individuals older (younger) than their reported age at cessation (onset) are classified as non-smokers. Smoking cessation hence is determined by the date of the interview when respondent's age is equal to the reported age at cessation.

The focus of the present analysis is smoking cessation, which is why the estimation sample is restricted to cigarette smokers until they quit smoking or leave the study.<sup>3</sup> For each individual only one spell of smoking can be considered (from age at onset to age at cessation), as the retrospective nature of the data does not permit the observation of multiple spells of smoking and non-smoking.<sup>4</sup> The dependent variable of the empirical model is a binary indicator that switches from zero to one if an individual quits smoking. In all previous observations the dependent variable is zero, indicating smoking continuation. The final estimation sample consists of 1,980 individual smoking histories (12,409 person-year observations), of whom 531 individuals quit smoking during the period under consideration.

### 4.2.2 Health Events

SHP survey participants state whether or not they have suffered from health problems, and report month and year of onset of the health event. If a health problem has occurred, participants additionally

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<sup>1</sup>The Swiss Household Panel (SHP) is based at the Swiss Centre of Expertise in the Social Sciences FORS and financed by the Swiss National Science Foundation.

<sup>2</sup>Since questions concerning the key explanatory variable, i.e. the occurrence of a health event, were introduced in 2000, the first wave (1999) is not considered.

<sup>3</sup>Individuals who reported smoking only cigars or pipes are not considered, since it is not clear how to compare cigarette smokers to pipe or cigar smokers in terms of consumption levels and habits and with respect to addiction.

<sup>4</sup>Similar approaches are adopted by Douglas and Hariharan (1994), who analyze the hazard of taking up smoking, Douglas (1998), who investigates the hazard rates for starting and quitting smoking, Forster and Jones (2001), who estimate tax elasticities for both taking up and quitting smoking and Marti (2013), who estimates the impact of tobacco control expenditures on individual smoking behavior in Switzerland.

Table 4.1: Health Events and Smoking Cessation

|             | No HE           | Physical HE  | Mental HE   | Accident     | Total           |
|-------------|-----------------|--------------|-------------|--------------|-----------------|
| (0) Smoking | 10,778 (95.9%)  | 676 (92.1%)  | 83 (98.8%)  | 341 (95.8%)  | 11,878 (95.7%)  |
| (1) Quit    | 457 (4.1%)      | 58 (7.9%)    | 1 (1.2%)    | 15 (4.2%)    | 531 (4.3%)      |
| Total       | 11,235 (100.0%) | 734 (100.0%) | 84 (100.0%) | 356 (100.0%) | 12,409 (100.0%) |

Notes: Author's calculations based on the SHP. The table shows the cross-tabulation of the binary dependent variable and the different health events.

report the type of health event they experienced and select one of the following categories: physical reasons, mental reasons, four different types of accidents, and other unspecified reasons.<sup>5</sup> Unspecified health events (243 cases) are excluded from the empirical analysis, as they provide no basis for forming a hypothesis.<sup>6</sup> Due to questioning, an individual can report only one of these health events in the period between two interviews, but may experience different health events during the period under consideration.<sup>7</sup>

This information is used to construct two sets of health event indicators. The first one includes a single binary variable indicating whether any type of health event has occurred since the last interview (1,174 cases). This variable is the result of collapsing the different kinds of health events into one binary indicator and might be comparable to an overall measure of suffering from health problems that is derived from a drop in self-assessed health (Sundmacher, 2012; Hsieh, 1998; Clark and Etilé, 2002). However, this does not allow to analyze whether changes in health behavior depend on the type of information received (health event experienced) by the individual. Therefore, separate and mutually exclusive indicators for physical (734 cases) and mental health events (84 cases), and a further dummy variable representing any kind of accident (356 cases) enter the second set of health event indicators.<sup>8</sup>

To get a first impression of the relationship between the key explanatory variables and the dependent variable of the model, Table 4.1 shows a simple cross-tabulation. Each cell comprises absolute and relative frequencies, where the latter refer to the respective column instead of to the full sample to simplify comparison between the two potential outcomes (smoking cessation/continuation). Overall, health events occur in roughly 10 percent of the observations ( $(734+84+356)/12,409 \approx 0.1$ ), providing sufficient variation for estimation purposes. As can be seen, the share of quitters among those who suffer from a physical health event is almost twice as large as compared to those without any type of health problem (7.9% vs. 4.1%), providing a first indication for a positive relationship between experiencing physical health problems and smoking cessation. In contrast, the results suggest a negative correlation between the decision to quit smoking and suffering from mental health problems (1.2% vs. 4.1%). However, column four also reveals that the data exhibits an almost quasi-complete separation problem (Albert and Anderson, 1984) with respect to mental health problems.<sup>9</sup> There is only one individual who quits smoking and simultaneously suffers from a mental health problem, which challenges identification of the effect of mental problems on the decision to stop smoking empirically. Finally, the occurrence of an

<sup>5</sup>Physical and mental reasons are not specified in more detail. Accidents are subdivided into work accidents, road accidents, sport accidents, and accidents at home or in the garden.

<sup>6</sup>Unreported estimation results show no relationship between unspecified health events and the inclination to stop smoking.

<sup>7</sup>In case of several health events between two interviews, SHP participants are supposed to select the most serious health problem.

<sup>8</sup>The four types of accidents are collapsed into one binary variable.

<sup>9</sup>Quasi-complete separation would be present if there is no individual that suffers from mental health problems and simultaneously quits smoking.

Table 4.2: Descriptives

| Variable  | Mean | S.D. | Min. | Max. |
|---|------|------|------|------|
| Age < 25 (base category)                        |      |      |      |      |
| Age 25-34                                       | 0.14 | 0.35 | 0    | 1    |
| Age 35-44                                       | 0.24 | 0.43 | 0    | 1    |
| Age 45-54                                       | 0.25 | 0.43 | 0    | 1    |
| Age 55-64                                       | 0.15 | 0.36 | 0    | 1    |
| Age $\geq$ 65                                   | 0.08 | 0.27 | 0    | 1    |
| Female  | 0.51 | 0.50 | 0    | 1    |
| Married   | 0.61 | 0.49 | 0    | 1    |
| Children  | 0.36 | 0.48 | 0    | 1    |
| Income 1 <sup>st</sup> quartile (base category) |      |      |      |      |
| Income 2 <sup>nd</sup> quartile                 | 0.25 | 0.43 | 0    | 1    |
| Income 3 <sup>rd</sup> quartile                 | 0.25 | 0.43 | 0    | 1    |
| Income 4 <sup>th</sup> quartile                 | 0.25 | 0.43 | 0    | 1    |
| Higher education                                | 0.12 | 0.33 | 0    | 1    |
| Swiss citizenship                               | 0.88 | 0.32 | 0    | 1    |
| French-speaking (base category)                 |      |      |      |      |
| German-speaking                                 | 0.65 | 0.48 | 0    | 1    |
| Italian-speaking                                | 0.05 | 0.21 | 0    | 1    |
| Unemployed                                      | 0.03 | 0.16 | 0    | 1    |
| Pregnant  | 0.01 | 0.08 | 0    | 1    |
| Time at risk (in 10 years)                      | 2.38 | 1.40 | 0    | 7.4  |

Notes: Author's calculations based on the SHP. Figures shown relate to the full estimation sample of 12,409 person-year observations.

accident seems to be uncorrelated with smoking cessation (4.2% vs. 4.1%), indicating that individuals do not react to health problems that are likely to be unrelated to smoking behavior.

### 4.2.3 Confounding Variables

The set of standard controls comprises indicator variables for females, having children, being married and a dummy for Swiss citizenship. Age enters the regression in terms of six categories for individuals aged younger than 25 years (base category), 25-34 years, 35-44 years, 45-54 years, 55-64 years and 65 years and older. In order not to impose a linearity assumption with respect to individual's income, I use indicator variables representing the four income quartiles in the estimation sample (base category: 1<sup>st</sup> quartile). Education enters the model through another binary variable representing higher education, which applies to individuals with more than 17 years of formal education. A set of fixed canton and time effects completes the set of standard controls.

In addition, several other potential confounding variables enter the regression model. Pregnancy provides a strong motive to quit smoking, but may also lead to a higher vulnerability to negative health events. Since women are not explicitly asked whether they are pregnant, I follow the approach of Sundmacher (2012) in assuming pregnancy in period  $t$  if a child under the age of one enters the household in  $t + 1$ . Another potential confounding factor might be unemployment. Marcus (2012) finds that unemployment affects smoking initiation and observes a positive – although not significant – effect on smoking continuation. Against the large body of literature that highlights the negative effects of unemployment on health (e.g. Green, 2011; Marcus, 2013), a separate indicator for unemployment enters the model. Furthermore, a growing body of literature considers the relationship between smoking behavior and both ethnicity and culture. Christopoulou and Lillard (2013), for example, find that culture can predict smoking participation, while Hymowitz et al. (1997) observe no significant effect of ethnicity

on smoking cessation. To allow culture to be related to the probability of reporting or experiencing a health event, I exploit the coexistence of four national languages in Switzerland as a proxy for cultural differences and include a set of language dummies (base category: French-speaking).<sup>10</sup> Finally, I account for the addictive nature of tobacco consumption and include the cubic polynomial of the number of years an individual has already been smoking (*time at risk*).<sup>11</sup> Descriptive statistics of all control variables are provided in Table 4.2.

### 4.3 Empirical Specification

Getting away from tobacco consumption is modeled in the fashion of a discrete time hazard model (Allison, 1982), with smoking cessation as the absorbing state. More formally, choosing a logit specification, the probability of smoking cessation in period  $t$ , conditional on observables  $Z_{it}$  and conditional on not having stopped smoking in previous periods, is expressed as

$$P(y_{it} = 1|Z_{it}) \equiv \pi_{it} = \frac{1}{1 + \exp(-Z'_{it}\theta)} = \frac{1}{1 + \exp(-(\alpha + HE'_{it}\beta + TaR'_{it}\delta + X'_{it}\gamma))} \quad (4.1)$$

with subscript  $i$  denoting individuals. The coefficient vector of interest is  $\beta$ , representing the effect of different health events ( $HE_{it}$ ) on the decision to quit smoking. The vector  $TaR_{it}$  includes the cubic polynomial of the number of years an individual has already been smoking (*time at risk*) and serves as baseline hazard rate.  $X_{it}$  contains the set of standard controls and further potential confounding variables, as outlined in the previous section.

The data exhibits an almost quasi-complete separation problem, as experiencing a mental health problem almost perfectly predicts non-failure, that is smoking continuation. In case quasi-complete separation is existent, applying the usual maximum likelihood estimator results in estimated parameters and standard errors of the separating variables that will be of infinite size (Zorn, 2005). To tackle this problem, the paper makes use of *Firth's* method (Firth, 1993), which was originally developed to reduce small-sample bias in maximum likelihood estimation. However, *Firth's* method has also been advocated to address estimation problems due to the presence of complete and quasi-complete separation (Heinze and Schemper, 2002; Zorn, 2005; Heinze, 2006). Basically, this method maximizes a modified (penalized) log-likelihood function

$$\ln L(\theta|y)^P = \ln L(\theta|y) + 0.5 \ln |I(\theta)| \quad (4.2)$$

that consists of the log-likelihood function  $\ln L(\theta|y)$  of the ordinary logit model and the log-determinant of the corresponding information matrix  $\ln |I(\theta)|$ . The latter acts as 'penalizing term' that takes its maximum value if the event probability  $\pi_{it}$  is 0.5 for all observation and, hence, penalizes small and large fitted probabilities in the estimation of  $\theta$ . This becomes obvious from the simple form the information matrix takes for the logit model  $I(\theta) = Z'WZ$ , with  $Z$  representing the regressor matrix and  $W$  denoting the weighting matrix  $\text{diag} \{ \pi_{it}(1 - \pi_{it}) \}$ . Augmenting the objective function by  $0.5 \ln |I(\theta)|$  hence

<sup>10</sup>Roughly two-thirds of the Swiss population speak German. French is spoken by about 20 percent of the population. About 7 percent of the population speak Italian, and a minority of 0.5 percent speaks Romansh.

<sup>11</sup>Similar approaches are adopted by Sundmacher (2012) and Marti (2013).

counteracts the shortcoming of estimated coefficients of infinite absolute size – and in turn degenerated estimated probabilities of zero or one, respectively – in the presence of quasi complete separation. Zorn (2005) shows that the penalized likelihood approach yields consistent estimates in the presence of complete or quasi-complete separation, and that the estimated coefficients converge to the usual maximum likelihood estimates as the sample size goes to infinity.<sup>12</sup>

Identifying the effect of health events on smoking cessation mainly rests on two key assumptions. First, one has to rule out that the health event is a consequence of smoking cessation. Both smoking cessation and the health event occur in the same period of time, that is between two interview dates, which may raise concerns about reverse causality. Applying an instrumental variable approach is not feasible in the present analysis due to missing instruments that are sufficiently correlated with the experience of different health events and simultaneously fulfill the exclusion restriction. Although the issue of potential reverse causality cannot be solved entirely, several arguments are provided in subsection 4.4.2 for why reverse causality, even if present, should not be a crucial issue in this application.

The second key assumption requires that no unobservable factors exist that simultaneously affect both, the occurrence of a health event and the decision to quit smoking. An example for such unobservable factors might be personality traits such as risk aversion. Risk aversion has been found to be related to smoking behavior (Van Loon et al., 2005; Ida et al., 2011), and one might also hypothesize that risk-loving individuals are more likely, for instance, to experience a physical health event. In this case, the estimation results would suffer from omitted variable bias. Including a measure for individual's risk preferences is not practicable due to too many missing values in the corresponding variable. Another common approach is assuming such personality traits to be time-invariant and including individual fixed effects to account for this type of unobservables. Since applying a fixed effects approach is not possible in non-repeated event history analysis (Allison and Christakis, 2006), I opt for performing additional placebo regressions to put more credibility on the assumption that no time-invariant confounding variables exist.

## 4.4 Results

This section begins with the main estimation results obtained from the model outlined in the previous section. Additionally, the results of several robustness checks stressing the model's underlying identifying assumptions are discussed.

### 4.4.1 Main Results

Table 4.3 presents the estimation results using the two sets of health event indicators. Panel A shows the results when including one binary indicator representing the experience of any type of health event ( $HE_{all}$ ), while three mutually exclusive indicator variables ( $HE_{physical}$ ,  $HE_{mental}$ ,  $HE_{accidents}$ ) are used in Panel B. Each panel, in turn, shows the results of four specification that differ with respect to the set of control variables. In column (1) no controls enter the model, column (2) accounts for individual

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<sup>12</sup>Excellent descriptions of Firth's method are provided by Heinze and Schemper (2002), and Zorn (2005). To estimate the empirical model, I use the add-on package `firthlogit` for Stata (Coveney, 2008). Any data or computational errors are of course my own.

Table 4.3: Results - Estimated Coefficients

|                     | (1)              | (2)              | (3)              | (4)              |
|---------------------|------------------|------------------|------------------|------------------|
| Panel A             |                  |                  |                  |                  |
| $HE_{all}$          | 0.467*** (0.129) | 0.518*** (0.130) | 0.496*** (0.131) | 0.477*** (0.133) |
| Panel B             |                  |                  |                  |                  |
| $HE_{physical}$     | 0.712*** (0.144) | 0.788*** (0.146) | 0.770*** (0.147) | 0.751*** (0.149) |
| $HE_{mental}$       | -0.860 (0.825)   | -0.713 (0.827)   | -0.727 (0.827)   | -0.861 (0.830)   |
| $HE_{accidents}$    | 0.067 (0.264)    | 0.052 (0.265)    | 0.021 (0.266)    | 0.021 (0.269)    |
| Individual controls |                  | ✓                | ✓                | ✓                |
| Time at risk        |                  |                  | ✓                | ✓                |
| Canton and time FE  |                  |                  |                  | ✓                |

Notes: Author's calculation based on the SHP. The estimation sample consists of 12,409 observations from 1,980 individuals of whom 531 quit smoking. The table shows the results of eight specifications of the discrete time hazard model. Panel A includes the binary indicator representing any kind of health event. In Panel B the overall measure is replaced by three binary indicators representing physical health events, mental disorders and accidents, respectively. Full regression outputs of Panel A and B are presented in Table 4.6 and 4.7, respectively. Standard errors in parentheses, \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

characteristics, in column (3) the cubic polynomial of time at risk is added, and column (4) represents the full specification that also includes the sets of canton and time fixed effects.

Beginning with Panel A, the estimated coefficient of the health event indicator is positive and statistically different from zero. This is in line with previous empirical findings to the extent that general self-perceived deterioration of health increases (on average) the probability of smoking cessation (Hsieh, 1998; Clark and Etilé, 2002; Sundmacher, 2012). Moreover, comparing the estimation results across the four columns it can be seen that the coefficient estimate of experiencing a health problem is not sensitive to different sets of control variables.

To go one step further and to analyze whether different types of health events affect the probability of smoking cessation differently, Panel B reports the results using three separate health event indicators. The estimated coefficient of physical health events exhibits a positive sign and is highly significant, indicating that individuals who suffer from physical health problems are more likely to quit smoking than those who have no health problems. More precisely, the estimated coefficient is roughly one and a half times larger than the one obtained from the overall measure ( $HE_{all}$ ) in Panel A. In contrast, the estimated coefficient of mental health problems is negative but of similar absolute magnitude as the one of physical health problems. Yet, the large estimated standard error renders the coefficient estimate insignificant, which is likely attributable to the fact that only one individual quits smoking while suffering from a mental health problem. As already indicated by the descriptive results, accidents do not induce changes in smoking behavior. The estimated coefficient is virtually zero and statistically insignificant. Again, the results remain unaffected by the set of control variables that enters the model.

For non-linear models the raw coefficient estimates do not tell much about the magnitude of the effects under consideration. To get a first impression of what the estimated coefficients imply in quantitative terms, Table 4.4 reports average marginal effects of the four model specifications presented in Panel B of Table 4.3. As indicated by the estimated coefficients, the average marginal effects are not sensitive to different sets of control variables. In the preferred specification (4), the average marginal effect of physical health problems amounts to 0.035 and is – as already suggested by the regression results – highly significant. Suffering from physical health problems increases the probability of smoking cessation by about 3.5 percentage points on average, which may appear as rather small impact at first

Table 4.4: Results - Marginal Effects

|                  | (1)              | (2)              | (3)              | (4)              |
|------------------|------------------|------------------|------------------|------------------|
| $HE_{physical}$  | 0.034*** (0.009) | 0.038*** (0.010) | 0.037*** (0.010) | 0.035*** (0.011) |
| $HE_{mental}$    | -0.023 (0.015)   | -0.020 (0.017)   | -0.020 (0.017)   | -0.023 (0.016)   |
| $HE_{accidents}$ | 0.003 (0.010)    | 0.002 (0.010)    | 0.001 (0.010)    | 0.001 (0.010)    |

Notes: Author's calculation based on the SHP. The estimation sample consists of 12,409 observations from 1,980 individuals of whom 531 quit smoking. The table presents average marginal effects of the four model specifications as shown in Panel B of Table 4.3.

sight. However, against the average predicted probability to quit smoking, which amounts to 0.042 in the present sample, this is an effect of considerable magnitude. Although lower in absolute magnitude as compared to physical health problems, the average marginal effect of mental disorders (-0.023) can still be considered as substantial. Yet, and as expected from the estimated coefficients, the average partial effect of mental health problems is statistically not significant. This also holds if the marginal effect is not evaluated at its average but on its most advantageous point. Finally, the average partial effect of accidents is almost zero and insignificant (0.001), suggesting that individuals do not adjust their smoking behavior after the occurrence of an accident.

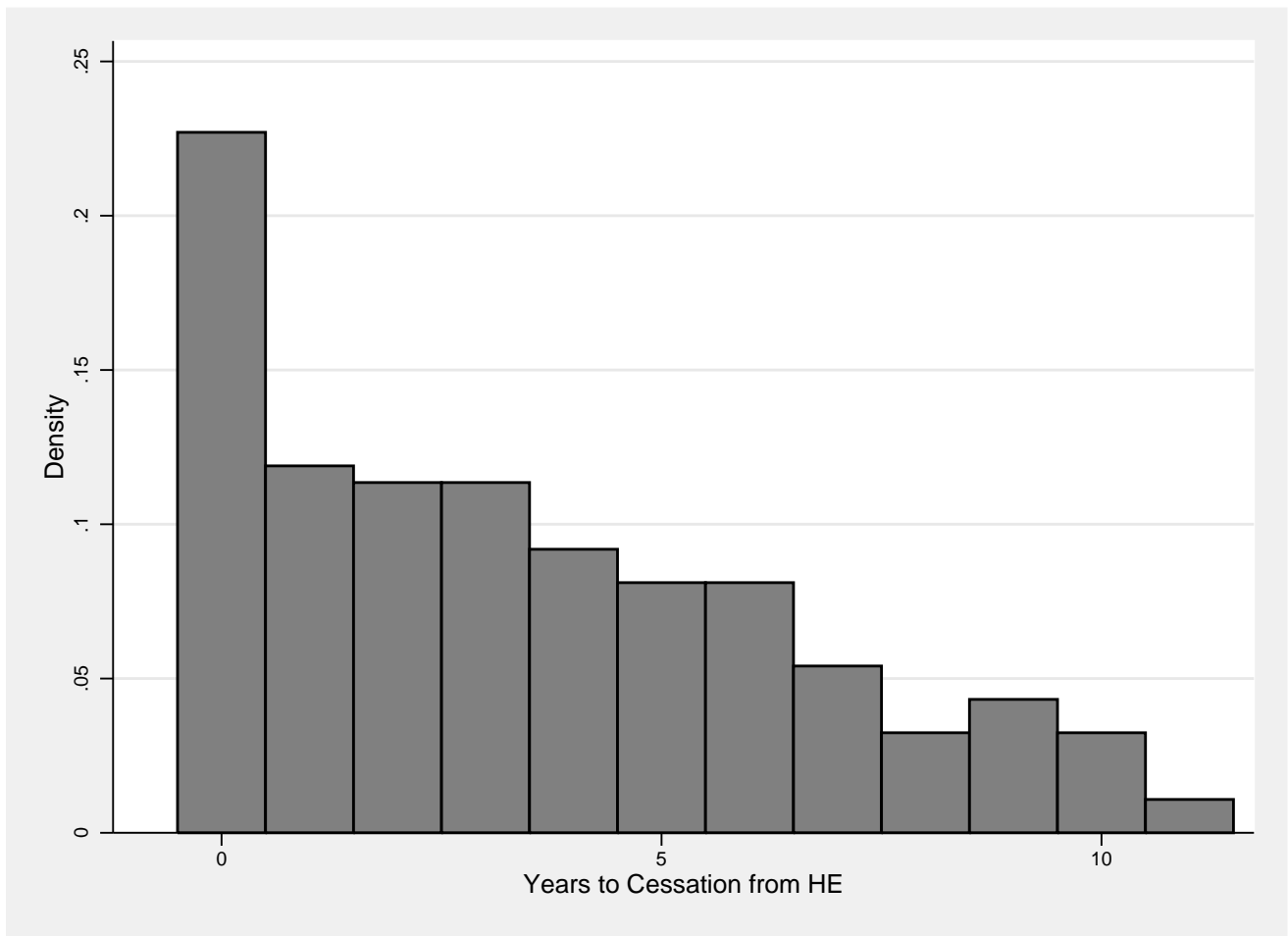
To put it into a nutshell, the estimation results provide clear evidence that physical health problems induce behavioral change among smokers. Individuals who suffer from physical problems have a significant higher probability to quit smoking, which is reasonable as this is the type of health problem among those under scrutiny, which is most closely related to own health behavior. The results with respect to mental health problems are less conclusive. The absolute magnitude of the estimated effect is considerable and points towards a negative relationship between mental problems and smoking cessation. This is plausible as individuals who suffer from mental problems are likely to avoid additional stress induced by withdrawal symptoms due to smoking cessation. Yet, the lack of significance does not allow for an unambiguous conclusion. Accidents have virtually no effect on the inclination to stop smoking, supporting the idea that individuals do not change their health behavior as a consequence of health problems that are most likely unrelated to their own health behavior.

#### 4.4.2 Reverse Causality

As both the health event and the decision to quit smoking take place between two interview dates, the first main identifying assumption requires that the health event is not caused by smoking cessation.<sup>13</sup> Apart from using an instrumental variable, which is not available from the survey, a natural approach to ensure that the health event occurred before individuals quit smoking would be to use the lagged health event variable. However, smokers are expected to adjust their behavior immediately after the health event occurs, when awareness of this information is likely to be highest. This is also observed by Sundmacher (2012), who finds no effect for the lagged health event variable. For the present sample, Figure 4.1 shows smoking cessation by year of the health event. The heap at zero supports the notion that individuals respond rather directly to health events, hence, using the lagged health event seems not feasible.

<sup>13</sup>Although SHP participants also report month of onset of the health event, the exact timing, i.e. the month of smoking cessation is not available from the survey.



Figure 4.1: Quit Smoking by Year from Health Event ( $HE_{all}$ )

Notes: Own calculations based on the SHP. The figure shows the empirical distribution of the number of years between the health event and smoking cessation for those who quit smoking in the estimation sample.

Although not tackled empirically, reverse causality should not be a substantial problem in this analysis, as both effects are likely not to appear simultaneously. Health events are expected to lead to an immediate adjustment of smoking behavior, while the reverse effects of smoking cessation on the probability of suffering from a health event are likely to appear much later. The positive impact of smoking cessation on physical health, for instance, comes into effect only after a certain period of abstinence. Even if there are simultaneous effects in both directions, this is likely to result in conservative estimates, as they are expected to carry opposite signs. To be more concrete, physical health events, which might be related to smoking, increase the probability of smoking cessation. The reverse effect of improved health behavior, i.e. smoking cessation, on the probability of experiencing a physical problem can be assumed to be negative. The opposite relationship is expected to hold for mental health problems and smoking cessation. Although not significant different from zero, mental problems seem to affect the likelihood of smoking cessation negatively. This might be explained by the self-medicating character of tobacco consumption when suffering from mental disorders (Clark and Etilé, 2002). The reverse effect of smoking cessation on the probability of suffering from mental problems is expected to be positive, at least in the short run. Withdrawal symptoms associated with smoking cessation may induce stress and may affect mental balance, which in turn leads to a higher vulnerability to mental problems.

Table 4.5: Robustness Checks

|                 | Main Model          | Unobserved Confounders |                   | Misclassification Error |                     | Maximum Likelihood  |                     |
|-----------------|---------------------|------------------------|-------------------|-------------------------|---------------------|---------------------|---------------------|
|                 | (1)                 | (2)                    | (3)               | (4)                     | (5)                 | (6)                 | (7)                 |
| $HE_{physical}$ | 0.751***<br>(0.149) | 0.221<br>(0.191)       | -0.043<br>(0.225) | 0.713***<br>(0.181)     | 0.836***<br>(0.166) | 0.750***<br>(0.150) | 0.721***<br>(0.143) |
| $HE_{mental}$   | -0.861<br>(0.830)   | -0.169<br>(0.646)      | -0.044<br>(0.650) | -0.668<br>(0.836)       | -0.568<br>(0.831)   | -1.260<br>(1.012)   | -1.235<br>(1.003)   |
| $HE_{accident}$ | 0.021<br>(0.269)    | -0.158<br>(0.321)      | 0.004<br>(0.310)  | 0.177<br>(0.294)        | 0.081<br>(0.299)    | -0.010<br>(0.274)   | -0.000<br>(0.266)   |
| # Observations  | 12,409              | 10,892                 | 9,350             | 6,496                   | 11,775              | 12,409              | 12,409              |
| # Individuals   | 1,980               | 1,898                  | 1,795             | 1,696                   | 1,851               | 1,980               | 1,980               |
| # Quitters      | 531                 | 396                    | 341               | 322                     | 404                 | 531                 | 531                 |

Notes: Author's calculation based on the SHP. The table shows the estimated coefficients of 7 separate regressions. Column (1) shows the original estimates as reported in Table 4.3 (Panel B, column (4)). Column (2) and (3) present estimation results where the health events are pretended to have happened one and two periods earlier. Column (4) restricts the sample to 2007 - 2011. Column (5) drops all individuals who reported to quit at ages that are multiples of five. In column (6) and (7) the usual maximum likelihood techniques are applied by estimating a logit model (6) and a complementary log-log model column (7), respectively. All coefficients are regression-adjusted, full regression output is presented in Table 4.8. Standard errors in parentheses, \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

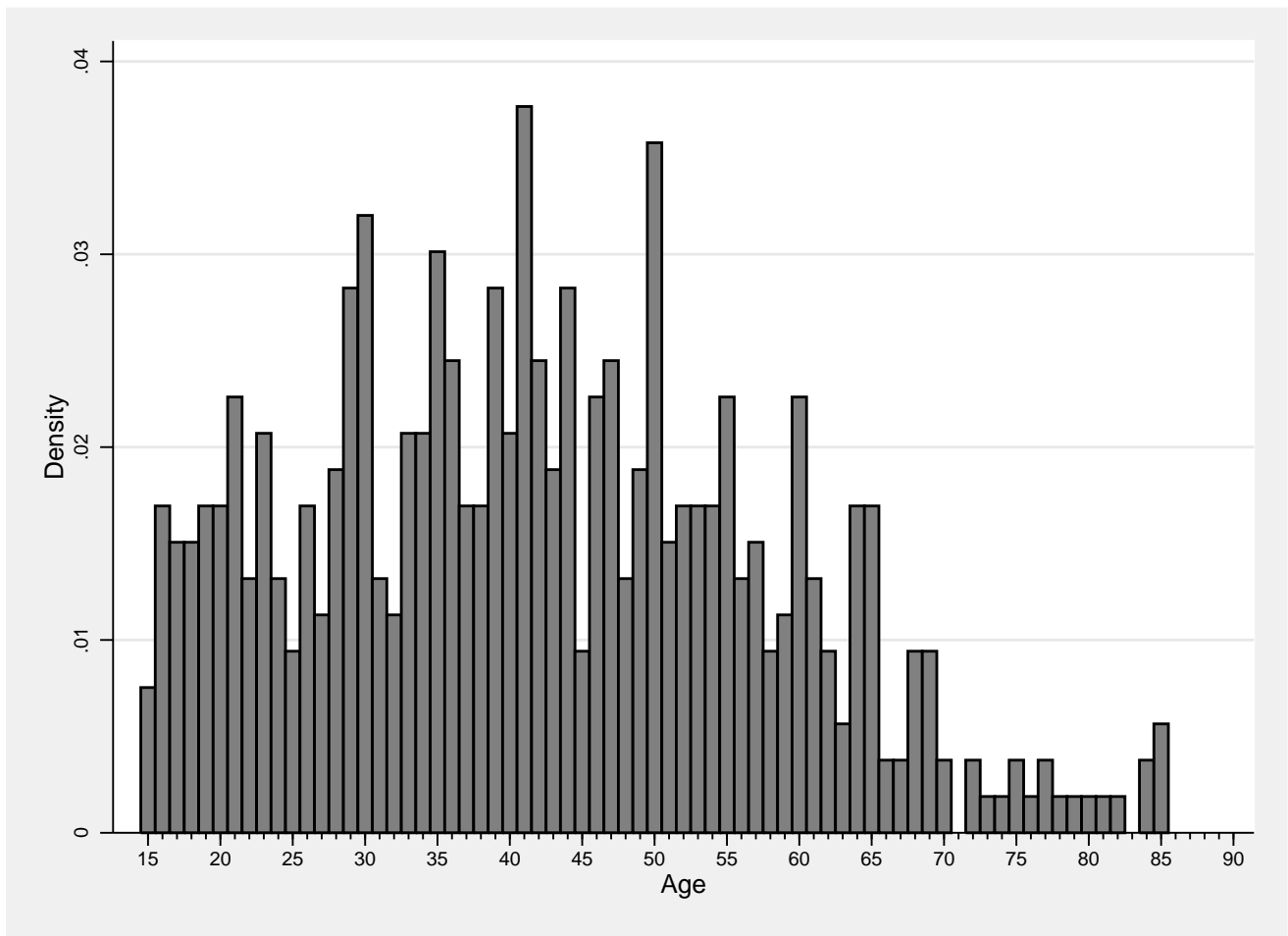
#### 4.4.3 Unobserved Confounders

The second main identifying assumption imposes that no unobservable factors exist that simultaneously affect the probability of suffering from a health event and the decision to quit smoking, that is the model controls for all relevant confounding variables. Typically, potential omitted variable bias is addressed by including individual fixed effects that relax this assumption by removing those unobservable confounders that are time-invariant. Since including individual fixed effects is not possible in this analysis, I opt for conducting two placebo regressions to put more credibility on this assumption. The first one pretends that the health events have occurred one period earlier, while the second one pretends them to have happened two periods earlier. The intuition behind this approach is that if such time-invariant confounders exist, the estimated coefficients of the placebo health events are expected to be significantly different from zero. As can be seen in column (2) and (3) of Table 4.5, the estimated coefficients are substantially smaller in absolute magnitude and not significant different from zero. This does not fully hold for accidents, as the estimated coefficient is larger in column (2) as compared to the main model. However, the coefficient estimate remains small and the large standard error renders the estimated coefficient insignificant. Altogether, this can be interpreted as further evidence that no unobservable time-invariant factors exist that simultaneously affect both the experience of a health event and the inclination to stop smoking. Hence, the results seem not to be heavily influenced by omitted variables bias.

#### 4.4.4 Misclassification Error

Individual smoking histories are constructed using retrospectively reported information on smoking behavior, which has been found to be a useful source for research on cigarette addiction (Kenkel et al., 2003, 2004). A potential drawback of using retrospectively reported information, however, is that individuals may not remember correctly when they took up and quit smoking, and one may hypothesize that the resulting measurement error in the dependent variable bias the empirical results. Misclassification error is likely influenced by how questions to past smoking behavior are posed. Lopez Nicolas

Figure 4.2: Age at Smoking Cessation



Notes: Own calculations based on the SHP. The figure shows the empirical distribution of age at smoking cessation in the estimation sample.

(2002) suspects that questions like *“How long ago did you stop smoking?”* might result in heaps at multiples of 5. This is also documented by Grignon (2009), who observe clear heaps at multiples of 5 as a respond to the question *“For how many years have you been a smoker?”*.

The SHP’s personal questionnaire asks participants *“At what age did you last smoke regularly?”*, which may lead to similar heaps at ages that are multiples of 5, and hence might bias the estimation results. To get a first impression whether misclassification might be a severe problem in the present analysis, Figure 4.2 shows the distribution of age at cessation for the estimation sample. Although heaps at certain prominent ages at cessation are indeed present (e.g. 30 or 35), they seem to be of tolerable extent as compared to other studies and indicate no crucial problem due to misclassification error in the dependent variable. Yet, I perform two additional robustness checks to assess sensitivity of the empirical results with respect to potential misclassification error. In column (4) of Table 4.5, the model is re-estimated restricting the sample to the period from 2007 to 2011. The idea behind this approach is to reduce potential misclassification, as only individuals are considered who quit smoking during the last five years and, hence, should remember more precisely when they stopped smoking. The estimated coefficients, in particular the coefficient estimate of physical health events, are close to what I found in the main specification, providing a first indication that misclassification is not a crucial issue. As second ad-hoc approach, column (5) presents the results excluding individuals from the estimation

sample who reported to have quit smoking at ages that are multiples of 5 (Kenkel et al., 2011). Again, the results are very similar to those obtained from the unrestricted sample, indicating that the original results are not affected heavily by misclassification error in the dependent variable.

#### 4.4.5 Maximum Likelihood Estimation

The main results are obtained from a logit model that accounts for the problem of almost quasi-separation with respect to mental health events by maximizing a penalized likelihood function. In order to assess the sensitivity of the results, I also estimate the model using the usual maximum likelihood techniques. More precisely, I apply the usual logit as well as the complementary log-log model. The former serves as direct benchmark to the modified logit model applied in this analysis. The latter is chosen as it takes into account the large share of non-failures in the data, which might also influence the empirical results.<sup>14</sup> Results are presented in column (6) and (7) of Table 4.5. In column (6), the results show that ignoring the problem of almost quasi-separation would lead to a substantial overestimation of the effect of mental health problems. The coefficient estimate is almost 50 percent larger as compared to the main model, while the respective standard error increases by roughly 20 percent. Except for the estimated coefficient of the separating variable (mental health events), the remaining coefficient estimates are close to those obtained from applying *Firth's* method (Zorn, 2005). Considering the results of the complementary log-log model in column (7), I observe almost identical estimation results as in the logit model in column (6). This can be interpreted such that the present analysis does not suffer from too few failures (smoking cessation) in the data.

## 4.5 Conclusion

Tobacco consumption is the second most important risk factor for deaths worldwide (World Health Organization, 2009), translating to more than 5 million deaths each year. To reduce smoking prevalence, and thereby public health expenditures, it is important to evaluate which strategies might be effective tools in the fight against tobacco consumption. This paper investigates whether new health information in terms of health problems can induce behavioral change among smokers.

Based on data from the SHP, individual smoking histories are constructed by exploiting retrospectively reported information on age at smoking onset and age at cessation. To test whether health problems motivate smokers to quit at all and whether behavioral change depends on the type of health event experienced, I use three different sorts of health events: physical health problems, mental disorders, and accidents. The inclination to quit smoking is modeled in the fashion of a discrete time hazard model. To account for estimation problems arising from almost quasi-complete separation with respect to mental health problems, a modified version of the log-likelihood function of the ordinary logit model is estimated.

The estimation results clearly indicate that smokers respond to health information in terms of health events. That is, individuals who suffer from any type of health problem have a significant higher probability of instantaneous smoking cessation as compared to those who report no health problem.

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<sup>14</sup>Although the linear probability model seems not to be an appropriate model for the present analysis (Horrace and Oaxaca, 2006), unreported regression results remain qualitatively and quantitatively similar when applying OLS.

Distinguishing between what causes the health event reveals that the overall effect is mainly driven by physical health problems. This seems reasonable to the extent that physical health problems can be considered as the type of health event that is most closely related to own health behavior. Moreover, the effect of suffering from a mental health problem is substantial in absolute magnitude, pointing towards a negative effect on smoking cessation, but is statistically not significant. The negative sign might be explained by the self-medicating character of tobacco consumption when suffering from mental disorders. Finally, the effect of experiencing an accident is virtually zero, indicating that individuals do not adjust their health behavior as a consequence of a health event that is likely not related to own health behavior. These results remain qualitatively and quantitatively robust when the model's underlying key identifying assumptions are stressed.

Individuals adjust their smoking behavior as a result of health problems. This is an important and relevant finding, as it suggests that individuals adjust their health behavior as a consequence of new health information. Reactions are strongest for information that is most closely related to own health behavior. In the context of the fight against tobacco consumption, information campaigns hence seem to be an appropriate tool to reduce smoking prevalence. For instance, shocking pictures on cigarette packages that confront consumers directly with the harmful physical health consequences of their own health behavior could be an effective tool to increase smoker's risk perception. However, one has to bear in mind that health events are an extreme case of health information and hence should be considered as an upper bound for the effectiveness of information campaigns (Smith et al., 2001).

## 4.6 Appendix

Table 4.6: Full Estimation Results: Panel A

|                                 | (1)               | (2)               | (3)               | (4)               |
|---------------------------------|-------------------|-------------------|-------------------|-------------------|
| $HE_{all}$                      | 0.467*** (0.129)  | 0.518*** (0.130)  | 0.496*** (0.131)  | 0.477*** (0.133)  |
| Age 25-34                       |                   | -0.253 (0.181)    | -0.464* (0.243)   | -0.329 (0.243)    |
| Age 35-44                       |                   | -0.526*** (0.175) | -0.862*** (0.304) | -0.658** (0.306)  |
| Age 45-54                       |                   | -0.816*** (0.181) | -1.232*** (0.339) | -1.085*** (0.341) |
| Age 55-64                       |                   | -0.607*** (0.192) | -1.133*** (0.373) | -0.965** (0.376)  |
| Age $\geq$ 65                   |                   | -0.346 (0.221)    | -1.192*** (0.439) | -1.096** (0.442)  |
| Female                          |                   | -0.018 (0.100)    | -0.007 (0.101)    | -0.030 (0.102)    |
| Married                         |                   | 0.359*** (0.112)  | 0.355*** (0.112)  | 0.376*** (0.114)  |
| Children                        |                   | 0.013 (0.107)     | 0.029 (0.108)     | 0.066 (0.109)     |
| Income 2 <sup>nd</sup> quartile |                   | -0.055 (0.144)    | -0.050 (0.146)    | -0.056 (0.147)    |
| Income 3 <sup>rd</sup> quartile |                   | 0.169 (0.152)     | 0.172 (0.154)     | 0.155 (0.155)     |
| Income 4 <sup>th</sup> quartile |                   | 0.422*** (0.158)  | 0.433*** (0.160)  | 0.417*** (0.161)  |
| Higher education                |                   | 0.201 (0.131)     | 0.201 (0.131)     | 0.175 (0.133)     |
| Swiss citizenship               |                   | -0.019 (0.141)    | -0.038 (0.142)    | 0.009 (0.145)     |
| German-speaking                 |                   | 0.106 (0.100)     | 0.116 (0.101)     | 0.214 (0.269)     |
| Italian-speaking                |                   | -0.198 (0.253)    | -0.186 (0.254)    | -0.057 (0.512)    |
| Unemployed                      |                   | 0.046 (0.300)     | 0.049 (0.300)     | -0.005 (0.303)    |
| Pregnant                        |                   | 1.561*** (0.311)  | 1.567*** (0.311)  | 1.706*** (0.314)  |
| Time at risk                    |                   |                   | 0.423 (0.373)     | 0.329 (0.379)     |
| Time at risk <sup>2</sup>       |                   |                   | -0.133 (0.130)    | -0.117 (0.133)    |
| Time at risk <sup>3</sup>       |                   |                   | 0.017 (0.013)     | 0.017 (0.013)     |
| Constant                        | -3.160*** (0.048) | -3.152*** (0.223) | -3.275*** (0.244) | -3.206*** (0.431) |
| Canton and time FE              |                   |                   |                   | ✓                 |
| # Observations                  | 12,409            | 12,409            | 12,409            | 12,409            |
| # Individuals                   | 1,980             | 1,980             | 1,980             | 1,980             |
| # Quitters                      | 531               | 531               | 531               | 531               |

Notes: Author's calculation based on the SHP. The table shows full regression results of four specifications shown in Panel A of Table 4.3. Standard errors in parentheses, \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

Table 4.7: Full Estimation Results: Panel B

|                                 | (1)               | (2)               | (3)               | (4)               |
|---------------------------------|-------------------|-------------------|-------------------|-------------------|
| $HE_{physical}$                 | 0.712*** (0.144)  | 0.788*** (0.146)  | 0.770*** (0.147)  | 0.751*** (0.149)  |
| $HE_{mental}$                   | -0.860 (0.825)    | -0.713 (0.827)    | -0.727 (0.827)    | -0.861 (0.830)    |
| $HE_{accident}$                 | 0.067 (0.264)     | 0.052 (0.265)     | 0.021 (0.266)     | 0.021 (0.269)     |
| Age 25-34                       |                   | -0.253 (0.181)    | -0.470* (0.244)   | -0.335 (0.244)    |
| Age 35-44                       |                   | -0.530*** (0.176) | -0.871*** (0.304) | -0.668** (0.307)  |
| Age 45-54                       |                   | -0.827*** (0.181) | -1.239*** (0.338) | -1.088*** (0.341) |
| Age 55-64                       |                   | -0.623*** (0.192) | -1.140*** (0.372) | -0.961** (0.376)  |
| Age $\geq$ 65                   |                   | -0.376* (0.221)   | -1.222*** (0.439) | -1.114** (0.442)  |
| Female                          |                   | -0.022 (0.100)    | -0.011 (0.101)    | -0.039 (0.102)    |
| Married                         |                   | 0.355*** (0.112)  | 0.348*** (0.112)  | 0.372*** (0.114)  |
| Children                        |                   | 0.019 (0.107)     | 0.036 (0.108)     | 0.074 (0.109)     |
| Income 2 <sup>nd</sup> quartile |                   | -0.058 (0.144)    | -0.053 (0.146)    | -0.058 (0.147)    |
| Income 3 <sup>rd</sup> quartile |                   | 0.172 (0.152)     | 0.175 (0.154)     | 0.158 (0.155)     |
| Income 4 <sup>th</sup> quartile |                   | 0.427*** (0.158)  | 0.438*** (0.160)  | 0.422*** (0.161)  |
| Higher education                |                   | 0.201 (0.131)     | 0.199 (0.131)     | 0.172 (0.133)     |
| Swiss citizenship               |                   | -0.016 (0.141)    | -0.035 (0.142)    | 0.011 (0.145)     |
| German-speaking                 |                   | 0.103 (0.100)     | 0.113 (0.101)     | 0.210 (0.270)     |
| Italian-speaking                |                   | -0.198 (0.253)    | -0.187 (0.254)    | -0.070 (0.512)    |
| Unemployed                      |                   | 0.086 (0.300)     | 0.087 (0.300)     | 0.044 (0.304)     |
| Pregnant                        |                   | 1.558*** (0.311)  | 1.564*** (0.311)  | 1.707*** (0.314)  |
| Time at risk                    |                   |                   | 0.451 (0.375)     | 0.363 (0.382)     |
| Time at risk <sup>2</sup>       |                   |                   | -0.146 (0.132)    | -0.134 (0.134)    |
| Time at risk <sup>3</sup>       |                   |                   | 0.019 (0.013)     | 0.019 (0.014)     |
| Constant                        | -3.160*** (0.048) | -3.144*** (0.223) | -3.275*** (0.244) | -3.218*** (0.431) |
| Canton and time FE              |                   |                   |                   | ✓                 |
| # Observations                  | 12,409            | 12,409            | 12,409            | 12,409            |
| # Individuals                   | 1,980             | 1,980             | 1,980             | 1,980             |
| # Quitters                      | 531               | 531               | 531               | 531               |

Notes: Author's calculation based on the SHP. The table shows full regression results of four specifications shown in Panel B of Table 4.3. Standard errors in parentheses, \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

Table 4.8: Full Estimation Results: Robustness Checks

|                           | Main Model           | Unobserved Confounders |                      | Misclassification Error |                      | Maximum Likelihood   |                      |
|---------------------------|----------------------|------------------------|----------------------|-------------------------|----------------------|----------------------|----------------------|
|                           | (1)                  | (2)                    | (3)                  | (4)                     | (5)                  | (6)                  | (7)                  |
| $HE_{physical}$           | 0.751***<br>(0.149)  | 0.221<br>(0.191)       | -0.043<br>(0.225)    | 0.713***<br>(0.181)     | 0.836***<br>(0.166)  | 0.750***<br>(0.150)  | 0.721***<br>(0.143)  |
| $HE_{mental}$             | -0.861<br>(0.830)    | -0.169<br>(0.646)      | -0.044<br>(0.650)    | -0.668<br>(0.836)       | -0.568<br>(0.831)    | -1.260<br>(1.012)    | -1.235<br>(1.003)    |
| $HE_{accident}$           | 0.021<br>(0.269)     | -0.158<br>(0.321)      | 0.004<br>(0.310)     | 0.177<br>(0.294)        | 0.081<br>(0.299)     | -0.010<br>(0.274)    | -0.000<br>(0.266)    |
| Age 25-34                 | -0.335<br>(0.244)    | -0.424<br>(0.304)      | -0.611*<br>(0.334)   | 0.020<br>(0.291)        | -0.581**<br>(0.277)  | -0.340<br>(0.245)    | -0.328<br>(0.235)    |
| Age 35-44                 | -0.668**<br>(0.307)  | -0.793**<br>(0.371)    | -0.847**<br>(0.402)  | -0.226<br>(0.387)       | -1.125***<br>(0.359) | -0.680**<br>(0.308)  | -0.652**<br>(0.297)  |
| Age 45-54                 | -1.088***<br>(0.341) | -1.238***<br>(0.409)   | -1.274***<br>(0.440) | -0.690<br>(0.428)       | -1.852***<br>(0.410) | -1.110***<br>(0.342) | -1.074***<br>(0.330) |
| Age 55-64                 | -0.961**<br>(0.376)  | -1.260***<br>(0.447)   | -1.128**<br>(0.475)  | -0.469<br>(0.473)       | -2.102***<br>(0.468) | -0.987***<br>(0.377) | -0.949***<br>(0.365) |
| Age ≥ 65                  | -1.114**<br>(0.442)  | -1.217**<br>(0.524)    | -0.986*<br>(0.555)   | -0.657<br>(0.552)       | -2.616***<br>(0.566) | -1.143**<br>(0.445)  | -1.104**<br>(0.431)  |
| Female                    | -0.039<br>(0.102)    | -0.013<br>(0.119)      | -0.078<br>(0.129)    | -0.001<br>(0.128)       | 0.009<br>(0.116)     | -0.040<br>(0.102)    | -0.039<br>(0.099)    |
| Married                   | 0.372***<br>(0.114)  | 0.366***<br>(0.132)    | 0.345**<br>(0.142)   | 0.357**<br>(0.147)      | 0.445***<br>(0.131)  | 0.377***<br>(0.115)  | 0.368***<br>(0.111)  |
| Children                  | 0.074<br>(0.109)     | 0.044<br>(0.124)       | 0.024<br>(0.133)     | 0.075<br>(0.143)        | -0.001<br>(0.123)    | 0.074<br>(0.109)     | 0.069<br>(0.106)     |
| Income 2 <sup>nd</sup> q. | -0.058<br>(0.147)    | -0.137<br>(0.174)      | -0.025<br>(0.188)    | -0.126<br>(0.183)       | -0.113<br>(0.168)    | -0.058<br>(0.148)    | -0.054<br>(0.144)    |
| Income 3 <sup>rd</sup> q. | 0.158<br>(0.155)     | 0.215<br>(0.179)       | 0.307<br>(0.192)     | 0.029<br>(0.199)        | 0.174<br>(0.176)     | 0.161<br>(0.156)     | 0.156<br>(0.151)     |
| Income 4 <sup>th</sup> q. | 0.422***<br>(0.161)  | 0.483***<br>(0.183)    | 0.416**<br>(0.200)   | 0.249<br>(0.208)        | 0.431**<br>(0.184)   | 0.428***<br>(0.162)  | 0.415***<br>(0.157)  |
| Higher education          | 0.172<br>(0.133)     | 0.207<br>(0.149)       | 0.279*<br>(0.160)    | 0.119<br>(0.173)        | 0.191<br>(0.152)     | 0.169<br>(0.134)     | 0.161<br>(0.129)     |
| Swiss citizenship         | 0.011<br>(0.145)     | 0.100<br>(0.174)       | 0.364*<br>(0.210)    | -0.059<br>(0.177)       | -0.016<br>(0.163)    | 0.019<br>(0.146)     | 0.018<br>(0.141)     |
| German-speaking           | 0.210<br>(0.270)     | 0.192<br>(0.320)       | -0.136<br>(0.350)    | -0.052<br>(0.356)       | 0.282<br>(0.308)     | 0.211<br>(0.270)     | 0.204<br>(0.260)     |
| Italian-speaking          | -0.070<br>(0.512)    | -0.019<br>(0.604)      | -0.361<br>(0.701)    | -0.525<br>(0.715)       | -0.052<br>(0.580)    | -0.122<br>(0.513)    | -0.122<br>(0.499)    |
| Unemployed                | 0.044<br>(0.304)     | -0.056<br>(0.384)      | -0.145<br>(0.446)    | 0.270<br>(0.329)        | 0.110<br>(0.331)     | 0.008<br>(0.310)     | 0.021<br>(0.301)     |
| Pregnant                  | 1.707***<br>(0.314)  | 1.696***<br>(0.309)    | 1.657***<br>(0.331)  | 2.048***<br>(0.432)     | 1.702***<br>(0.348)  | 1.700***<br>(0.320)  | 1.606***<br>(0.289)  |
| Time at risk              | 0.363<br>(0.382)     | 0.396<br>(0.468)       | 0.824<br>(0.514)     | -0.136<br>(0.475)       | 0.401<br>(0.445)     | 0.357<br>(0.384)     | 0.340<br>(0.369)     |
| Time at risk <sup>2</sup> | -0.134<br>(0.134)    | -0.073<br>(0.170)      | -0.244<br>(0.185)    | -0.049<br>(0.163)       | -0.051<br>(0.157)    | -0.128<br>(0.135)    | -0.122<br>(0.130)    |
| Time at risk <sup>3</sup> | 0.019<br>(0.014)     | 0.008<br>(0.018)       | 0.025<br>(0.020)     | 0.014<br>(0.016)        | 0.010<br>(0.016)     | 0.018<br>(0.014)     | 0.017<br>(0.013)     |
| Constant                  | -3.218***<br>(0.431) | -3.760***<br>(0.482)   | -3.881***<br>(0.534) | -1.584**<br>(0.676)     | -3.341***<br>(0.492) | -3.262***<br>(0.433) | -3.284***<br>(0.419) |
| Canton and time FE        | ✓                    | ✓                      | ✓                    | ✓                       | ✓                    | ✓                    | ✓                    |
| # Observations            | 12,409               | 10,892                 | 9,350                | 6,496                   | 11,775               | 12,409               | 12,409               |
| # Individuals             | 1,980                | 1,898                  | 1,795                | 1,696                   | 1,851                | 1,980                | 1,980                |
| # Quitters                | 531                  | 396                    | 341                  | 322                     | 404                  | 531                  | 531                  |

Notes: Author's calculation based on the SHP. The table shows full regression results of seven specifications shown in Table 4.5. Standard errors in parentheses, \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .



## Chapter 5

# Does the Burglar Also Disturb the Neighbor? Crime Spillovers on Individual Well-being

### 5.1 Introduction

Crime activities account for large individual and societal costs all around the world. According to the U.S. Bureau of Justice the direct financial costs of crime to victims amounted to \$16bn and to \$179bn in government expenditures on police protection and the criminal justice system in 2007 (U.S. Department of Justice, 2007, 2008). While these direct, or tangible, costs of crime; i.e., property losses, medical bills and foregone income for the victim and the judicial, legal and correctional costs for the society of upholding law and order, are in themselves substantial, there are also other, intangible, costs which further contribute to the overall costs of crime. In particular, Dubourg et al. (2005) estimated that, based on QALY's and information reported in the British Crime Survey (BCS), the physical and emotional impact of crime against victims of crime composes more than half of the total costs of crime in the U.K – or approximately three percent of GDP (£36bn) in 2003. In addition, McCollister et al. (2010) found that tangible costs constituted only 12-47 percent of the total costs to victims in the U.K., depending on crime type. In contrast, the criminal justice system and the net value of lost property only accounted for twenty and ten percent of the total crime costs, respectively.<sup>1</sup>

Even when such *realized* (tangible and intangible) costs have been accounted for, *anticipatory* costs, relating to the psychological responses that criminal activity inflict through a fear of victimization among both victims and non-victims, remain unaccounted for (see e.g. Dolan et al., 2005). Anticipa-

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This study is joint work with Daniel Avdic. See Avdic and Bünnings (2015) for a working paper version of this chapter.

<sup>1</sup>In this context it is also interesting to note that estimates from contingent valuation surveys have typically found that respondents' value their willingness to reduce crime in their community much higher than officially stated costs of crime. One such example is Cook and Ludwig (2000), who, based on survey respondents' willingness to pay to reduce local crime, found the total costs of crime to victims to be \$694bn annually, or about forty times the direct victimization costs estimated by the U.S. Bureau of Justice.

tory responses to crime can be categorized into behavioral responses, occurring whenever an individual changes behavior due to fear of crime (e.g. avoiding to go out at night, using the car rather than walking or bicycling, developing mistrust in others and reducing participation in social activities); or psychological responses, in which an individual's mental well-being is affected through the fear of crime (e.g. increased mental distress, worry or the development of depression symptoms). A host of sociological studies have, theoretically and empirically, investigated the mechanisms through which crime affects psychological outcomes through the fear of crime (see e.g. Aneshensel and Sucoff, 1996; Schulz et al., 2000; Ross, 2000; Ross and Mirowsky, 2001; Green et al., 2002; Whitley and Prince, 2005; Stafford et al., 2007; Jackson and Stafford, 2009). The general message from this literature is that individuals who worry more about crime also rate their mental health lower than other individuals, hence suggesting that costs of crime to non-victims might significantly contribute to the direct and indirect costs of victimization.

In this paper we contribute to the growing literature on quantifying the intangible costs of crime by investigating how variation in local crime rates affects psychological well-being in a previously largely unexplored country: Germany.<sup>2</sup> To avoid cross-sectional sorting and confounding of individuals with varying mental health in areas with different crime levels, we utilize panel data on local crime rates from the German Federal Criminal Police Office and measures of mental health from the German Socio-Economic Panel linked using residential zip codes of the respondents. Using actual crime rates as a proxy for fear of crime, rather than self-reported fear from crime surveys, to estimate effects on mental health has the benefit that we are unlikely to capture other changing attitudes towards crime and social trends or bias in reporting behavior when comparing responses between groups (see e.g. Farrall et al., 1997; Farrall and Gadd, 2004; Sutton and Farrall, 2005). Moreover, most existing studies have focused on urban areas which normally only constitute a small part of a country. Even if most crimes occur in cities, it is not *a priori* clear that any psychological effects derived from a fear of crime are greatest in such places. Some authors have argued that individuals exposed to high level of crime may develop coping strategies or a resilience towards 'incivilities', which allow them to reduce their stress levels in dangerous situations (Taylor, 1986; Taylor and Shumaker, 1990).<sup>3</sup> We explore this potential mechanism in detail by estimating psychological reactions to variation in crime rates – i.e. not crime levels – for the whole of Germany.

Recent contributions analyzing the causal pathway from fear of crime to mental health by using variation in local crime rates over time have found changes in crime rates to significantly affect subjective mental well-being among the local population. In particular, Cornaglia et al. (2014), using Australian data, estimate a disparity of the aggregate costs from indirect victimization of more than eighty times the direct costs of victimization. Similarly, Dustmann and Fasani (2013) apply data from the U.K. and find that changes in local crime rates affect residents' mental health 2-4 times more than comparable variation in local unemployment rates. Hence, these findings suggest that crime may impact whole communities and, when aggregated, potentially constitutes a much greater and unaccounted cost factor than the costs attributable to direct victims of crime.

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<sup>2</sup>Using the same data sources (German Socio-Economic Panel and German Federal Criminal Police Office), Krekel and Poprawe (2014) analyze the effect of local crime on satisfaction with life and satisfaction with the living environment.

<sup>3</sup>Taylor and Shumaker (1990) argues that "...the nonexistent or extremely weak linkage repeatedly observed between local crime levels and fear may reflect perceptual adaptation to the chronic hazard of local crime. Part of the perceptual adaptation, for some crimes, may be driven by the inoculating effects of prior exposure."

Our estimated results indicate, similar to Cornaglia et al. (2014) and Dustmann and Fasani (2013), that changes in local crime rates significantly affect the mental health of individuals living in the area. Results from our preferred specification imply that a one standard deviation increase in local crime rates significantly decreases individual mental well-being by one percent (0.442 MCS points) for violent crimes, while less strong impacts are found for property and total crime rates. The estimates correspond closely to the findings in Cornaglia et al. (2014), both qualitatively and quantitatively. As a comparison, we benchmark the magnitude of our effect of crime with other life events known to cause mental distress and find that the impact of a one standard deviation increase in violent crime corresponds to about half the effect from losing one's employment and one seventh of the effect from becoming a widow. Moreover, using an established preference-based method for quantifying the monetary equivalent of mental health, our estimates suggest a cost per violent crime of about €16,800 implying that the indirect psychological costs of violent crime only in Germany exceed €9bn per year.<sup>4</sup> Finally, our results are insensitive to a number of robustness checks we perform to address potential concerns in the interpretation of the estimated parameters. In particular, the results are not dependent on exclusion of the three city-states (Berlin, Hamburg and Bremen), territorial changes in some of the regions over time or by excluding movers from the estimation sample.

A common finding in the literature on fear of crime is that some groups in the society, in particular women, the elderly and the poor, report higher fear of crime than other (Pantazis, 2000; McCrea et al., 2005). Various social groups are likely to differ in their *perceived susceptibility* towards crime, i.e. in their subjective perceptions with respect to the likelihood of being targeted by criminals, their ability to control a threatening situation and the consequences of becoming a victim of crime (see e.g. Skogan and Maxfield, 1981; Warr, 1984, 1985, 1987; Killias, 1990; Ferraro, 1995; Smith and Torstensson, 1997; Jackson, 2009). To construct efficient policy tools that aim at reducing the overall adverse effects of crime on mental well-being it is crucial to understand the complexity behind the psychological mechanisms as to how fear of crime originates. As we additionally have access to a wide selection of socioeconomic characteristics from the respondents, we can explore in more detail the dynamics behind the channels through which fear of crime affects mental health. We find, in contrast to much of the previous literature, that men, more educated and childless individuals react more to variation in violent crimes in their neighborhood – while still being less fearful on average. We interpret this finding as suggesting that heterogeneous perceptions of actual victimization risks for particular crime types matter more than differences in the perceived consequences of victimization. Furthermore, we find that the fear effect is driven by less densely populated areas, which indicates some support for the 'resilience' hypothesis that individuals in urban areas are more used to and able to cope with higher levels of crime through 'cognitive habituation' (Taylor and Shumaker, 1990).

Our findings are of relevance for national and regional policies to reduce the negative effects of fear of crime on well-being in the society. In particular, we largely confirm recent empirical findings for Germany to the extent that costs to non-victims seem to amount to a considerable part of total costs of crime and should therefore be accounted for when estimating the total burden of crime to society. Furthermore, we find that type of crime, personal characteristics and population density seem to play

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<sup>4</sup>As a comparison, U.S. Department of Justice (1996), using data from the National Criminal Victimization Survey, estimated that the total victimization cost of criminal activity against individuals and households was \$450bn per year from 1987-1990, or \$1,800 per resident. Most of these costs (\$345bn) were incurred from pain, suffering and reduced quality of life of the victims.

fundamental roles in determining the individual fear and well-being response. Hence, even if some societal groups may be more fearful of crime as they perceive themselves as more vulnerable to victimization, other factors, such as coping behavior and perceptions of victimization risk of certain crime types, may counteract or even dominate such reactions. This interpretation finds support in a series of papers attempting to explain why victims of crime appear less fearful than non-victims (Denkers and Winkel, 1998a,b; Winkel, 1998, 1999; Winkel et al., 2003; Vrij and Winkel, 1991). Such insights into the complexity of the relationship between actual crime rates, fear of crime and its effects on mental well-being are important in order to develop fear-reducing policies which depend more on the physical, social and situational context at hand.

The paper is structured as follows. Section 5.2 describes the data we use for our empirical analysis, specifically the information from the German Socio-Economic Panel and the regional crime data we have at our disposal. Section 5.3 discusses the empirical approach we employ to estimate the impact of local crime rates on mental health outcomes. The main results, robustness checks and heterogeneity analyses are discussed in section 5.4. Section 5.5 concludes.

## **5.2 Data**

### **5.2.1 Data on Mental Well-Being and further Individual Controls**

This study is based on individual-level data from the German Socio-Economic Panel (SOEP) waves' 2004, 2006, 2008 and 2010. The SOEP is a nationally representative longitudinal survey initiated in 1984 which collects annual information on both the household and the individual level. Detailed information on different sets of categories, such as demographic and labor market characteristics as well as education, health and attitudes, are available for all household members aged 17 and older. Currently, the SOEP comprises more than 20,000 individuals from more than 10,000 households (Wagner et al., 2007).

To measure an individual's mental well-being we use the Mental Component Summary Scale (MCS), which originates from the SF-12v2 health survey contained in the SOEP. The SF-12v2 health survey consists of twelve questions, with six questions each relating to physical and mental well-being, respectively. The latter is assessed by four dimensions – mental health, role-emotional, social functioning, and vitality – which are aggregated to the summary scale MCS using explorative factor analysis (Andersen et al., 2007). Both the sub-scores and the summary scale range from 0 to 100, where a higher score indicates better health status, and are standardized with a mean of 50 and a standard deviation of 10 in the reference year 2004. The MCS is frequently used in empirical health economics studies (see e.g. Schmitz, 2011; Marcus, 2013) and has been found to be a good and consistent measure of an individual's mental health (see e.g. Gill et al., 2007; Salyers et al., 2000). The SF-12v2 health survey, and hence the MCS, was first implemented in the SOEP in 2002 and has henceforth been part of the individual questionnaire biannually. Descriptive statistics are provided in Panel (A) of Table 5.1.

Panel (B) of Table 5.1 lists a set of socioeconomic characteristics which we include to adjust for individual heterogeneity in our empirical analysis, in particular with respect to the markers of vulnerability; gender, age and socioeconomic status. Gender differences in fear of crime are captured by including a dummy for females. We account for age by including binary indicators representing four age

Table 5.1: Descriptive Statistics - Individuals

| Panel A: Mental Well-Being              | Mean  | S.D.  | Min.  | Max.  |
|---|-------|-------|-------|-------|
| Mental component summary (MCS)          | 50.21 | 10.02 | 1.92  | 79.43 |
| Social functioning (SF)                 | 49.83 | 10.18 | 14.69 | 57.12 |
| Vitality (VT)                           | 49.64 | 9.89  | 26.73 | 70.60 |
| Role emotional (RE)                     | 50.06 | 10.05 | 13.34 | 58.08 |
| Mental health (MH)                      | 50.12 | 9.96  | 19.73 | 68.58 |
| Panel B: Further Controls               |       |       |       |       |
| Female                                  | 0.52  | 0.50  | 0     | 1     |
| Age                                     |       |       |       |       |
| [31 - 45]                               | 0.28  | 0.45  | 0     | 1     |
| [46 - 60]                               | 0.28  | 0.45  | 0     | 1     |
| [61 - 75]                               | 0.22  | 0.41  | 0     | 1     |
| [76 - ]                                 | 0.07  | 0.26  | 0     | 1     |
| German citizenship                      | 0.94  | 0.24  | 0     | 1     |
| Higher education (high school and more) | 0.84  | 0.36  | 0     | 1     |
| Marital status                          |       |       |       |       |
| Single                                  | 0.21  | 0.41  | 0     | 1     |
| Widowed                                 | 0.07  | 0.25  | 0     | 1     |
| Divorced                                | 0.08  | 0.27  | 0     | 1     |
| Separated                               | 0.02  | 0.13  | 0     | 1     |
| Children at home                        | 0.29  | 0.45  | 0     | 1     |
| Occupation                              |       |       |       |       |
| Self-employed                           | 0.06  | 0.24  | 0     | 1     |
| Employee                                | 0.45  | 0.50  | 0     | 1     |
| Civil servant                           | 0.05  | 0.21  | 0     | 1     |
| Other (vocational training, etc.)       | 0.03  | 0.16  | 0     | 1     |
| Unemployed                              | 0.07  | 0.25  | 0     | 1     |

Notes: Own calculations based on the SOEP. Descriptive statistics refer to 72,362 person-year observations.

groups for individuals aged 31-45 years, 46-60 years, 61-75 years, and over 75 years (base category:  $\leq 30$ ). Furthermore, we control for marital status through indicator variables for being single, widowed, divorced, or separated (base category: married). We also include separate indicators for the presence of children at home and German citizenship and control for educational background through a dummy indicating high school or higher degree, and for labor market status through five occupational dummies (base category: not employed). In subsequent analyses, we also estimate separate models conditional on these socioeconomic characteristics in order to investigate potential heterogeneity in responses to actual crime as suggested by the literature on crime vulnerability.

### 5.2.2 Data on Crime and further County Controls

Official crime statistics are extracted from the annual police crime statistics (PCS).<sup>5</sup> The PCS is provided by the German Federal Criminal Police Office (“Bundeskriminalamt”) and based on data supplied from each of the sixteen State Offices of Criminal Investigations (“Landeskriminalamt”). Besides detailed information on a national level, such as the number of almost all recorded types of crime in Germany, the PCS also comprises an overview on selected crimes on a more disaggregated level (NUTS 3). More specifically, we collect information on the total number of crimes as well as the number of bodily

<sup>5</sup>See [http://www.bka.de/DE/Publikationen/PolizeilicheKriminalstatistik/pks\\_\\_node.html](http://www.bka.de/DE/Publikationen/PolizeilicheKriminalstatistik/pks__node.html)

Table 5.2: Descriptive Statistics - County

| Panel A: Crime Rates       | Mean      | S.D.     | Min.      | Max.      |
|----------------------------|-----------|----------|-----------|-----------|
| Total crime                | 7,510.63  | 3,284.00 | 2,367.00  | 29,352.00 |
| Violent crime              | 521.67    | 304.13   | 45.00     | 2,108.00  |
| Property Crime             | 1446.99   | 675.67   | 343.57    | 4,606.72  |
| Panel B: Further Controls  |           |          |           |           |
| Unemployment rate          | 10.84     | 5.03     | 1.90      | 31.40     |
| Income per capita          | 18,109.76 | 2,456.44 | 13,479.00 | 31,199.00 |
| Share of foreigners        | 8.47      | 5.41     | 0.70      | 26.20     |
| Age structure              | 56.78     | 7.42     | 34.80     | 86.80     |
| Males [0 - 19]             | 9.81      | 1.34     | 5.92      | 14.29     |
| Males [20 - 39]            | 12.82     | 1.47     | 9.46      | 17.92     |
| Males [40 - 59]            | 15.21     | 1.07     | 12.35     | 19.04     |
| Females [0 - 19]           | 9.32      | 1.26     | 5.51      | 13.53     |
| Females [20 - 39]          | 12.31     | 1.64     | 8.98      | 19.12     |
| Females [40 - 59]          | 14.87     | 0.94     | 12.24     | 18.24     |
| Total crime clearance rate | 56.78     | 7.42     | 34.80     | 86.80     |

Notes: Own calculations. Crime variables and clearance rates are extracted from the PCS. Further county characteristics are taken from "Regionaldatenbank" and INKAR 2011. Descriptive statistics refer to 72,362 person-year observations.

injuries, burglaries, thefts in/from cars, and the number of damages to property available for each of the 412 German counties ("Kreis") since 2004.<sup>6</sup>

Following Cornaglia et al. (2014) we measure crime by the number of crimes per 100,000 inhabitants (crime rate). We consider three types of crime in our regression model as shown in Panel (A) of Table 5.2: total crime, violent crime and property crime. The latter consists of the number of burglaries, thefts in/from cars and damages to property. Violent crime equals the number of bodily injuries and total crime covers all reported crimes on a county-year basis. Although we only have access to a small subset of crime categories, these are among the most frequent criminal offenses, covering roughly 25 percent ( $\approx 521.67+1446.99/7510.63$ ) of the total number of reported crimes.

In our analysis we also adjust for time-varying county characteristics that may be correlated with local crime rates and simultaneously affect mental well-being of inhabitants, as shown in Panel (B) of Table 5.2. The local unemployment rate enters the set of county characteristics to control for county-specific economic conditions that may affect both the level of crime (see e.g. Raphael and Winter-Ebmer, 2001; Gould et al., 2002) and individual's mental well-being (Clark and Oswald, 1994). Moreover, we include average income per capita to account for both financial distress (see e.g. Cornaglia et al., 2014) and local wages that have been found to be related to crime (see e.g. Grogger, 1998; Gould et al., 2002). The demographic structure is captured by the share of foreign-born and the age structure of the population, separated by gender. Additionally, to proxy for regional variation in quality of the criminal justice system we incorporate the total crime clearance rate.<sup>7</sup>

We link data on local crime rates and further county controls to the individuals in the SOEP by exploiting information on respondent's place of residence and the year of the interview. In particular, we use

<sup>6</sup>Until 2010, the category 'bodily injuries' refers to all bodily injuries. Since 2010, this category consists of dangerous and serious bodily injuries. This is not a problem for our analysis as this change applied to all counties simultaneously, and hence should be captured by the set of fixed calendar time effects we include in our models.

<sup>7</sup>The information on regional unemployment rates, average income per capita as well as the age structure of the population on county level is extracted from "Regionaldatenbank", available at: <https://www.regionalstatistik.de/genesis/online/logon>. Information on the share of foreigners is taken from INKAR 2011. Total crime clearance rate is extracted from the PCS.

an individual's zip code to identify the county of residence and link corresponding county crime rates for each interview year. In cases where an unambiguous assignment of individuals to counties based on the zip code was not possible, we exclude the respective individuals from the estimation sample.<sup>8</sup> Additionally, our observation period (2004-2010) covers two administrative reforms that changed the composition of counties in two federal states. In Saxony-Anhalt, this territorial reform became effective on July 1, 2007 and reduced the number of counties from 21 to 11 by amalgamating existing counties. In Saxony, a similar reform went into effect on August 1, 2008 and reduced the number of counties from 29 to 13. To be able to compare the affected counties before and after the reforms went effective, we apply the new territorial structure also to the years before the reforms actually took place.<sup>9</sup>

Our observation period covers the years 2004, 2006, 2008 and 2010 as these are the years in which the outcome variable, crime rates and individual zip-code information are available simultaneously. We end up with a final estimation sample consisting of 72,362 person-year observations from 26,842 different individuals. Overall, the sample covers 408 out of the 412 German counties representing over 99 percent of the German territory and population.<sup>10</sup>

### 5.3 Empirical Approach

To evaluate the impact of local crime on mental well-being we combine longitudinal information on regional crime statistics with individual level data representative of the whole of Germany. Specifically, we estimate a linear regression model, where mental health ( $mcs$ ) of individual  $i$  living in region  $r$  at time  $t$  is expressed by the following equation:

$$mcs_{irt} = \alpha + \beta_c crime_{rt} + \beta_x X'_{it} + \beta_z Z'_{rt} + \lambda_t + \lambda_r + \lambda_i + \lambda_r \times t + \varepsilon_{irt} \quad (5.1)$$

The key explanatory variable is  $crime_{rt}$ , a measure of local crime in region  $r$  at time  $t$ . We use three different types of crime rates: total crime, violent crime, and property crime. As outlined in section 5.2,  $X'_{it}$  and  $Z'_{rt}$  captures relevant time-varying individual characteristics, such as marital or employment status, and county characteristics, such as the unemployment rate or the demographic structure of the population, respectively.  $\lambda_t$ ,  $\lambda_r$ , and  $\lambda_i$  represent time, regional, and individual fixed effects, respectively. Finally, we also control for time-varying unobserved heterogeneity on county level, not already absorbed by the set of covariates included in  $Z'_{rt}$ , by including a full set of county-specific linear time trends. The regression error is denoted by  $\varepsilon_{irt}$ . To account for arbitrary correlations across observations within a region we estimate standard errors clustered at the county level.<sup>11</sup>

<sup>8</sup>We lose 2.5% of the observations due to zip codes that are not uniquely assignable to a county.

<sup>9</sup>To transform the affected county characteristics to the 'new' structure, we exploit that the amalgamating process took place mainly on county level, which allows to simply collapse the relevant variables. In cases where not all parishes of an existing county have been jointly assigned to a new county, we use parishes' population and territorial area to weight the variables accordingly.

<sup>10</sup>The SOEP is representative at the national level but may not be representative at the federal state level or even smaller geographical areas, such as counties. This constitutes no problem for our analysis, because inference is not conducted on county level but for Germany as a whole.

<sup>11</sup>In unreported regressions, we also use standard errors that are clustered at the individual level. The results remain robust and are available upon request.

The parameter of interest is  $\beta_c$ , the average impact of a unit change in local crime rates on individual mental well-being, which is identified under an IID assumption of the error term. Exploiting the longitudinal characteristics of our data we account for cross-sectional health sorting of individuals into areas with different crime rates. Assuming that variation in local crime rates are conditionally independent of individual mental health and that moving decisions are picked up by the individual fixed effects, we can consistently estimate  $\beta_c$ . Selective migration would not be captured by the individual fixed effects but, since only about one percent of the sampled individuals move across regions during the period under consideration, this should not cause any major problems for our empirical analysis. Nevertheless, we informally investigate the validity of this identifying assumption by performing a number of complementary robustness checks.

## 5.4 Results

### 5.4.1 Perceived vs. Actual Crime

Before turning to results from estimation we show some descriptive results on the observed relationship between actual crime rates and individual perceptions of crime from our estimation sample. As outlined in the introduction, fear of crime is considered to be the dominant underlying psychological mechanism through which actual crime affects mental well-being. Using self-reported fear of crime to estimate the psychological impact of crime may complicate identification due to correlations between fear and other confounding factors, such as more general attitudes toward social decay or differences in reporting behavior across groups. As our empirical analysis relies on changes in actual crime rates to estimate the indirect effects caused by fear of crime we can avoid much of these empirical difficulties. However, by using actual crime data we need to instead assume that crime rate variation is a valid proxy for changes in fear of crime. We assess the plausibility of this assumption by exploiting supplementary information on individuals' concerns about crime in Germany contained in the SOEP.

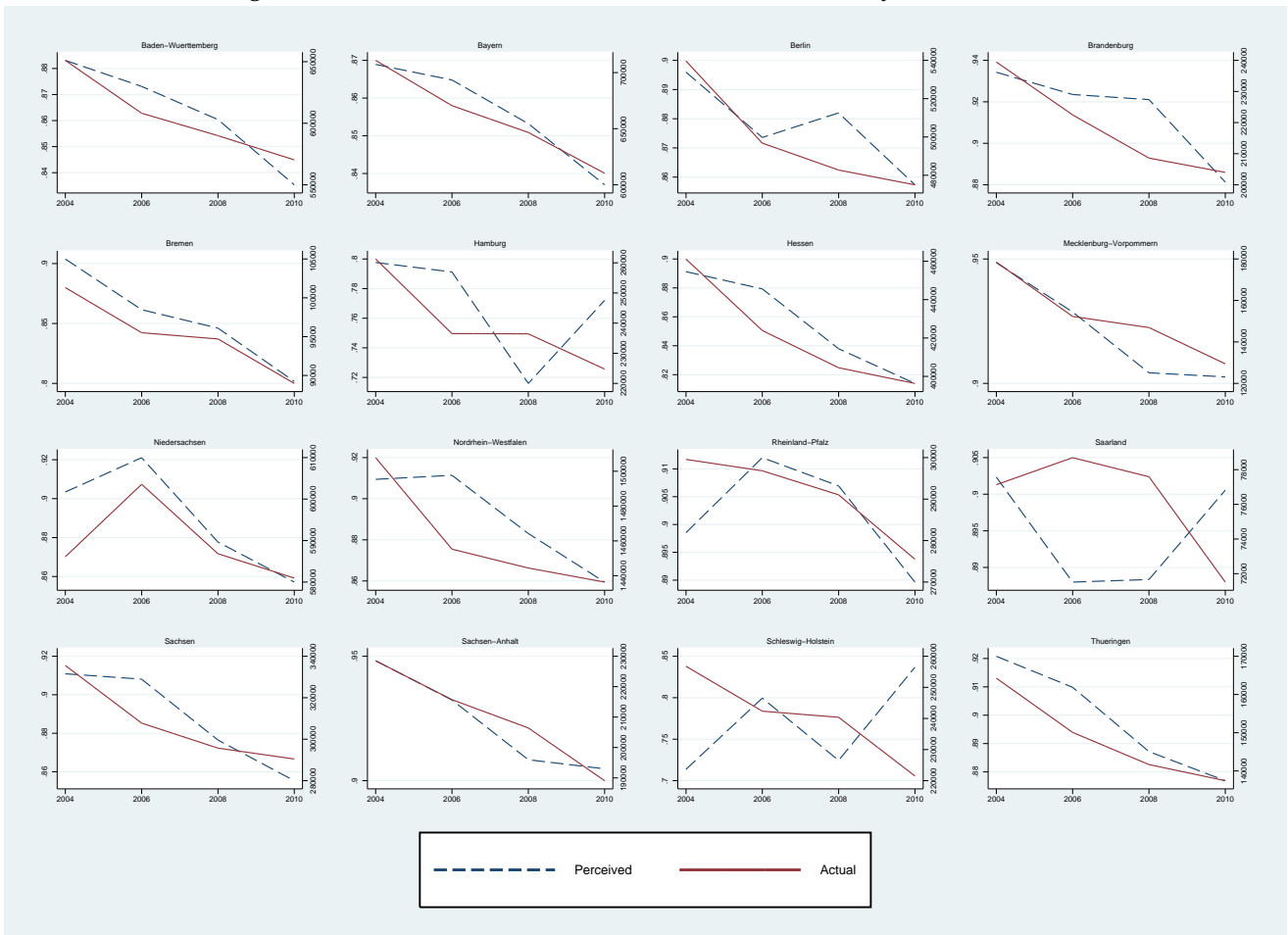
SOEP participants are asked whether they are 'very concerned', 'somewhat concerned' or 'not concerned at all' about crime in Germany. We collapse this information into a binary indicator reflecting any concerns about crime, which serves as benchmark for actual crime. Figure 5.1 shows the development of actual crime and the share of those expressing any concerns about crime in Germany separately for each of the 16 federal states (*Bundesland*). As can be seen, the trends of both graphs are very similar in almost all federal states indicating that changes in individuals' perception of crime are in accordance with changes in actual crime.<sup>12</sup> Apart from potential geographical differences in the perception of crime, certain societal groups perceive themselves as more vulnerable to victimization and, hence, develop a higher fear of crime. As mentioned in the introduction, higher levels of fear of crime among women, the elderly or individuals of lower socioeconomic status are well established findings in the literature (e.g. Warr, 1984; Pantazis, 2000; McCrea et al., 2005), although actual victimization rates are typically lower in most of these groups. In Figure 5.2 of the Appendix, we relate concerns about crime across these different societal groups and benchmark them to actual crime rates. As expected, women, the elderly and individuals with lower education typically worry more about crime in Germany, which

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<sup>12</sup>This does not fully hold for the federal states Saarland and Schleswig-Holstein, which may partly be explained by too few observations. We also assess sensitivity of the empirical results by excluding both states from the estimation sample. Results remain qualitatively and quantitatively robust and are available upon request.



Figure 5.1: Concerns about Crime vs Actual Crime by Federal State



Notes: Own calculations based on the SOEP and the PCS. The figure shows the number of actual crimes and the share of the population with at least some worries about crime in Germany separately for each of the 16 federal states of Germany.

is in line with the findings in the literature. Again, actual crime and worries about crime follow the same trend suggesting that actual crime is a credible proxy for fear of crime.

### 5.4.2 Main Results

Table 5.3 reports the results from 15 separate regressions using the combined mental health score (MCS) as the outcome variable. Each cell shows the results of a separate regression, where each of the three rows refers to a specific crime category (total, violent, property) and each of the six columns to a different model specification, ranging from the raw bivariate correlation in column (1) to the full set of control variables in column (6).

Most of the coefficient estimates show the expected negative sign, indicating a negative spillover effect from changes in local crime rates on individual mental well-being. Except for the coefficient of violent crime in our preferred specification (column 6), the estimated parameters are not statistically significant, however. This may reflect the relatively scarce variation in crime rates during the measurement period. Comparing the results across the six columns shows that the estimated coefficients are mainly driven by county characteristics rather than by individual controls; in particular for the

Table 5.3: The Effect of Crime Rates on Mental Well-Being

|                       | (1)               | (2)               | (3)               | (4)               | (5)               | (6)                 |
|-----------------------|-------------------|-------------------|-------------------|-------------------|-------------------|---------------------|
| Total Crime           | 0.004<br>(0.051)  | 0.007<br>(0.051)  | 0.023<br>(0.097)  | 0.003<br>(0.110)  | 0.012<br>(0.121)  | -0.038<br>(0.155)   |
| Violent Crime         | -0.017<br>(0.466) | -0.182<br>(0.709) | -0.667<br>(0.508) | -0.703<br>(0.513) | -0.797<br>(0.535) | -1.453**<br>(0.730) |
| Property Crime        | 0.155<br>0.253    | -0.167<br>(0.256) | 0.057<br>(0.415)  | -0.085<br>(0.487) | -0.064<br>(0.551) | -0.332<br>(0.442)   |
| Time FE               |                   | ✓                 | ✓                 | ✓                 | ✓                 | ✓                   |
| County FE             |                   |                   | ✓                 | ✓                 | ✓                 | ✓                   |
| Individual FE         |                   |                   |                   | ✓                 | ✓                 | ✓                   |
| Time-varying controls |                   |                   |                   |                   | ✓                 | ✓                   |
| Time trends           |                   |                   |                   |                   |                   | ✓                   |
| # Observations        | 72,362            |                   |                   |                   |                   |                     |

Notes: Own calculations based on data from the SOEP and the PCS. Each cell shows the estimated coefficient, multiplied by 1,000, of a separate regression. Altogether 15 regressions were performed. Standard errors clustered at the county level are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

estimated effect of violent crime rates. The latter estimate increases substantially when controlling for unobserved heterogeneity across regions in the form of both fixed county effects and county-specific linear time trends. This can be interpreted as indication that selection takes place to a great extent on the regional level, rather than within counties. In addition, the increasing absolute magnitude of the estimated coefficients from column (1) to (6) might indicate potential attenuation bias that shrinks the coefficient estimates towards zero. Hence, if additional confounding factors (*i*) exist and (*ii*) bias the results in the same direction as most of the variables in our model, then the reported results might constitute conservative estimates of the effect of local crime on mental well-being.<sup>13</sup> In the remainder of this section, we restrict our analysis to the preferred specification in column (6).

In order to assess the economic relevance of the estimated coefficients we pursue different strategies. We begin with considering the raw estimated coefficient as shown in Table 5.3 in more detail. The coefficient estimate of violent crime (1.453), which is multiplied by 1,000 for ease of illustration, implies that a one unit increase in violent crime rates decreases individual MCS, which ranges from 0 to 100, by approximately 0.0015 points, or 0.003 percent (evaluated at the mean), on average. This may appear as a rather small effect at first sight. Yet, taking into account that this is an average effect for all inhabitants and – more importantly – that a one unit increase in crime rates, which translates to one additional crime per 100,000 inhabitants, is an almost negligible change, the results indicate a considerable spillover effect of local crime on mental well-being when aggregated. Finally, our empirical results reinforce previous empirical findings. In particular, the point estimate of violent crimes is almost identical to the one estimated by Cornaglia et al. (2014). For property crimes we observe a larger but statistically insignificant effect, which is also in line with the results in Cornaglia et al. (2014).<sup>14</sup>

Following Dustmann and Fasani (2013), another way of quantitatively assessing the magnitude of the estimated effects is to relate them to the corresponding mental health impacts from two major

<sup>13</sup>One plausible explanation for this conservative bias could be that more resilient individuals tend to stay in high-crime areas while individuals with lower tolerance levels choose to reside in places with lower crime rates. This is also consistent with the results from the heterogeneity analysis reported below.

<sup>14</sup>However, Dustmann and Fasani (2013) find the overall effect to be mainly driven by property crime rather than violent crime rates. This may reflect differences in the definition of the crime categories.

Table 5.4: Quantifying the Effect of Crime on Mental Well-Being

|                             | (1)                  | (2)                  | (3)                  |
|-----------------------------|----------------------|----------------------|----------------------|
| Total Crime <sup>+</sup>    | -0.125<br>(0.509)    |                      |                      |
| Violent Crime <sup>+</sup>  |                      | -0.442**<br>(0.222)  |                      |
| Property Crime <sup>+</sup> |                      |                      | -0.225<br>(0.299)    |
| Unemployed                  | -0.890***<br>(0.317) | -0.886***<br>(0.317) | -0.890***<br>(0.317) |
| Widowed                     | -3.034***<br>(0.632) | -3.028***<br>(0.632) | -3.035***<br>(0.632) |
| # Observations              |                      | 72,362               |                      |

Notes: Own calculations based on data from the SOEP and the PCS. Each column shows the estimated coefficients of a separate regression. Altogether 3 regressions were performed. <sup>+</sup> indicates normalized variables. Standard errors clustered at the county level are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

life events (unemployment and losing one's partner). The results from this exercise are shown in Table 5.4. For ease of interpretation, we have normalized all crime variables to have mean zero and unit standard deviation, so that the estimated coefficients can be interpreted as the effect of an increase by one standard deviation in the respective crime category on mental well-being. Depending on the type of crime, the impact of an increase by one standard deviation ranges from one seventh (total crime) to one half (violent crime) of the estimated effect of becoming unemployed. More precisely, a one standard deviation increase in violent crime rates decreases MCS by 0.442 points, or approximately 0.9 percent (evaluated at the mean). Although slightly larger, the overall range of the estimated effect sizes (one seventh to one half) is similar to the one observed by Dustmann and Fasani (2013) (one seventh to one fifth).

Finally, we also provide a rough approximation of the monetary costs of the mental health effects to the society as a whole. To this end we estimate the monetary amount necessary to compensate individuals for a decrease in mental well-being as caused by the increase in crime rate. As we do not possess the necessary information to quantify what a marginal change in the MCS scale imply in monetary terms, we make use of the estimated value from Cornaglia et al. (2014), referring to a one percentage point loss in Social Functioning (SF).<sup>15</sup> Using their estimate, which is based on QALY of \$50,000 (Australian Dollars) and amounts to \$211 ( $\approx$  €142), seems also reasonable in our context as our main estimation results correspond closely, both qualitatively and quantitatively, to each other. To apply their measure, we first estimate the effect violent crime rates have on SF, which is one out of four sub-score of the MCS. As can be seen from Table 5.8 in the Appendix, a one unit increase in violent crime rates decreases SF by -0.00099 (s.e. 0.00082) percentage points, which is about two thirds of the effect estimated for the overall measure MCS. Using this estimate, we calculate that the society would be willing to pay around €16,800 to reduce violent crimes by one. Assuming that this amount represents a good approximation for the average cost of violent crime, our estimates imply that the total indirect psychological costs of bodily injuries amount to around €9bn in Germany in 2010. However, this estimate is evidently contingent on a number of crucial assumptions and should be interpreted carefully.

<sup>15</sup>More precisely, we do not have the necessary information to transform the SF-12 data into a SF-6D health state. The latter is a preference-based single index measure of health which can be used to calculate QALYs.

### 5.4.3 Sensitivity Analysis

To assess the sensitivity of the main results, Table 5.5 provides the results from several robustness checks. Column (1) serves as benchmark and shows the results of the main specification (cf. Table 5.3, column (6)).

A potential concern to our empirical strategy might be due to movers in our estimation sample. More precisely, our approach is valid as long as endogenous moving decisions are fully captured by the individual fixed effects and observed time-varying controls. To further assess the credibility of this assumption we report the estimation results restricting the sample to non-movers. We opt for the more conservative approach and exclude all individuals who move and not only those who move across counties. It is clear from column (2) of the table that excluding movers does not affect the estimation results – as expected given the low share of movers.

One may also worry that inferences may be driven by the three large German city states of Berlin, Hamburg and Bremen for which we have no further disaggregated data. These states are characterized by a relatively small territorial size, high population densities and high crime rates. Column (3) reports the results when excluding these states from the sample. Although qualitatively robust, the coefficient estimates are even larger in absolute magnitude as compared to the pooled sample. This is especially true for the estimated coefficient of violent crime, which increases by around 30 percent.<sup>16</sup>

As discussed in section 5.2, administrative reforms related to the territorial structure became effective during our observational period and decreased the number of counties in Saxony-Anhalt and Saxony in 2007 and 2008, respectively. To be able to compare affected counties before and after the respective reform went effective, we have superimposed the new territorial structure also in the years before the reform became effective. To test whether this affect our estimation results, we report the results obtained from the restricted estimation sample in column (4). Excluding both states does not affect the point estimates to any noticeable extent.

To ensure that the previous results are not predominantly driven by outliers, we also use a trimmed sample where we have excluded observations below the 5<sup>th</sup> and above the 95<sup>th</sup> percentile of the crime rate change distribution. From column (5) we see that the estimated coefficients and standard errors of the crime rates under consideration are very similar to those obtained from the unrestricted sample, hence indicating that outliers seem to play no crucial role in our estimation sample.

Finally, there might be concerns that part of the effect we capture originates from the effect of crime victims. Although we lack information on direct victimization in our data we believe that this should not severely bias our estimation results for several reasons: First, existing literature on the relationship between direct victimization and the perception of crime, especially the fear of crime, provides mixed results and point towards no clear connection (see e.g. Hill et al., 1985; Skogan, 1987; Box et al., 1988). Moreover, there are some indications that fear of crime is only weakly correlated with direct victimization (see e.g. Moore and Shepherd, 2006) but much more related to indirect victimization (see e.g. Hale, 1996). Second, the absolute magnitude of a potential bias induced by victims should be negligible as the share of victims in our estimation sample is likely to be considerably smaller than the share of non-victims. Third, our estimation results are unaffected by individual characteristics. Accordingly,

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<sup>16</sup>Hence, more dense regions seem to react less to changes in crime, indicating the existence of a resilience effect. We investigate this further below.

Table 5.5: Sensitivity Analysis

|                | Full<br>Sample<br>(1) | w/o<br>Movers<br>(2) | w/o<br>City States<br>(3) | w/o<br>Area Reforms<br>(4) | Trimmed<br>Sample<br>(5) |
|----------------|-----------------------|----------------------|---------------------------|----------------------------|--------------------------|
| Total Crime    | -0.038<br>(0.155)     | -0.033<br>(0.187)    | -0.041<br>(0.156)         | -0.044<br>(0.173)          | 0.013<br>(0.192)         |
| Violent Crime  | -1.453**<br>(0.730)   | -1.453**<br>(0.772)  | -1.916**<br>(0.815)       | -1.278<br>(0.805)          | -1.540*<br>(0.791)       |
| Property Crime | -0.332<br>(0.442)     | -0.280<br>(0.470)    | -0.358<br>(0.444)         | -0.339<br>(0.474)          | -0.303<br>(0.520)        |
| # Observations | 72,362                | 66,988               | 68,034                    | 64,276                     | 64,772                   |

Notes: Own calculations based on data from the SOEP and the PCS. Each cell shows the estimated coefficient, multiplied by 1,000, of a separate regression. Altogether 15 regressions were performed. Standard errors clustered at the county level are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

if these characteristics are correlated with the probability of becoming victimized and direct victimization effects were important, one would expect to find differences in the estimated impact of crime rates on mental well-being when adjusting for individual characteristics.

#### 5.4.4 Heterogeneity Analysis

##### Vulnerability to Crime

As mentioned in the introduction, a common finding in the literature is that various socioeconomic groups perceive different levels of fear of crime, although they do not differ in their exposure to crime. These differences might be explained by a higher perceived likelihood of becoming a victim or the feeling of being unable to protect themselves or their property against crime. Existing literature (e.g. Warr, 1984; LaGrange and Ferraro, 1989; Hale et al., 1994; Parker and Ray, 1990) has identified gender, age and socioeconomic status as markers of higher vulnerability to crime. Specifically, women, the elderly and individuals of lower socioeconomic status has been found to perceive particularly high levels of fear of crime, which also holds for our sample (cf. Figure 5.2 in the Appendix). Apart from differences in the absolute level of perceived fear of crime across various subgroups in the society it is important to understand how these subgroups react to changes in crime rates. This might be a helpful insight for policymakers into how to design more personalized and, hence, more effective interventions aiming at reducing fear of crime and its negative spillovers on mental well-being of individuals.

To investigate whether response to changes in crime rates also depend on these markers of vulnerability, we use information on gender, age, the presence of children at home and education. Each of the variables is used to split the original estimation sample into two sub-samples on which we reestimate the model and compare the coefficient estimates. The results of these split sample regressions along with the baseline results are presented in Table 5.6. With respect to the coefficient estimate of violent crime rates we find a significant effect for males, which is roughly 45 percent higher than the respective one obtained for females. Against the large body of literature that highlights higher vulnerability to crime of women, this may appear as rather counterintuitive at first sight. Yet, it is important to note that violent crimes in our data set only consists of bodily injuries, which usually have a higher prevalence among men, and does not cover sexual offenses, such as rape, which have been found to evoke

Table 5.6: Heterogeneous Responses to Crime with respect to Individual Characteristics

|                | Full Sample         | Gender              |                   | Age               |                   | Children            |                   | Education         |                     |
|----------------|---------------------|---------------------|-------------------|-------------------|-------------------|---------------------|-------------------|-------------------|---------------------|
|                |                     | Male                | Female            | < 50              | ≥ 50              | no                  | yes               | Low               | High                |
| Total Crime    | -0.038<br>(0.155)   | 0.072<br>(0.168)    | -0.157<br>(0.208) | -0.054<br>(0.166) | -0.030<br>(0.281) | 0.105<br>(0.214)    | -0.328<br>(0.228) | -0.122<br>(0.383) | -0.037<br>(0.159)   |
| Violent Crime  | -1.453**<br>(0.730) | -1.786**<br>(0.847) | -1.232<br>(0.925) | -1.029<br>(0.987) | -1.679<br>(1.042) | -1.821**<br>(0.834) | -0.856<br>(1.347) | -0.438<br>(2.261) | -1.681**<br>(0.732) |
| Property Crime | -0.332<br>(0.442)   | -0.233<br>(0.540)   | -0.416<br>(0.571) | -0.537<br>(0.615) | -0.136<br>(0.596) | 0.000<br>(0.528)    | -0.986<br>(0.825) | -0.115<br>(1.183) | -0.395<br>(0.450)   |
| # Obs.         | 72,362              | 34,868              | 37,494            | 37,016            | 35,346            | 51,554              | 20,808            | 11,397            | 60,965              |

Notes: Own calculations based on data from the SOEP and the PCS. Each cell shows the estimated coefficient, multiplied by 1,000, of a separate regression. Altogether 27 regressions were performed. Standard errors clustered at the county level are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

especially high levels of fear among women (Warr, 1985). We also observe larger coefficient estimates of violent crime rates for older individuals, those without children at home and individuals with high school diploma or higher education.

Apart from the larger effect for older individuals, these findings are – similar to those obtained for gender – contradicting expectations from the concept of vulnerability to crime. However, empirical findings with respect to the latter mainly rely on cross-sectional variation in crime rates while our analysis builds on changes in crime rates and their perceptions among different subgroups of the population. Hence, our results indicate that even if certain subgroups feel more vulnerable to victimization, other factors seem to counteract these reactions. For instance, although men or better educated individuals have been found to perceive lower levels of fear of crime, they might be more aware about the development of crime in their neighborhood and, hence, may react more to changes in local crime rates. In addition, certain subgroups, particularly those who perceive themselves as more vulnerable to victimization, such as women or those with children, may develop strategies and behaviors to protect themselves and their relatives from criminal victimization and to cope with crime in general. These coping strategies may also lead to lower sensitivity to changes in crime, although absolute levels of fear of crime may remain high.

### Geographical Size and Population Density

Most of the previous empirical literature on the relationship between crime, fear of crime and its spillover effects on individual's mental well-being has focused on metropolitan areas. Although densely populated areas are typically characterized by higher crime rates as compared to more rural areas, it is a priori not clear if negative spillover effects of crime on individual mental well-being are restricted to or particularly large in urban regions. Individuals who live in metropolitan areas and, hence, are subject to higher levels of crime, might also be more used to crime and might have developed strategies to cope with higher crime rates in their neighborhood. This, in turn, may imply that variation in crime in less densely populated areas, where crime rates are lower and individuals are less used to crime, may affect individual mental-wellbeing to a greater extent than in more urban environments. This notion is also supported by the greater, in magnitude, estimated coefficients observed in Table 5.5 where the three German city-states Berlin, Bremen and Hamburg were excluded. As our data set covers the

Table 5.7: Heterogeneous Responses to Crime with respect to County Characteristics

|                | Full Sample         | Territorial Size  |                    |                   |                   | Population Density |                      |                   |                   |
|----------------|---------------------|-------------------|--------------------|-------------------|-------------------|--------------------|----------------------|-------------------|-------------------|
|                |                     | Q-1               | Q-2                | Q-3               | Q-4               | Q-1                | Q-2                  | Q-3               | Q-4               |
| Total Crime    | -0.038<br>(0.155)   | 0.155<br>(0.170)  | -0.421<br>(0.380)  | -0.448<br>(0.454) | -0.093<br>(0.159) | 0.133<br>(0.375)   | -1.156***<br>(0.356) | 0.069<br>(0.272)  | 0.091<br>(0.205)  |
| Violent Crime  | -1.453**<br>(0.730) | -1.781<br>(1.348) | -1.687*<br>(0.997) | -1.774<br>(2.128) | -3.625<br>(2.433) | -2.018<br>(2.887)  | -6.191***<br>(2.479) | -2.360<br>(1.746) | -1.440<br>(0.966) |
| Property Crime | -0.332<br>(0.442)   | 0.076<br>(0.543)  | -1.216<br>(1.138)  | -1.474<br>(1.518) | -0.246<br>(1.387) | 1.706<br>(1.776)   | -3.997***<br>(1.097) | -0.222<br>(1.131) | -0.031<br>(0.551) |
| # Obs.         | 72,362              | 15,893            | 19,786             | 18,534            | 18,149            | 11,401             | 14,365               | 20,620            | 25,976            |

Notes: Own calculations based on data from the SOEP and the PCS. Each cell shows the estimated coefficient, multiplied by 1,000, of a separate regression. Altogether 27 regressions were performed. Standard errors clustered at the county level are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

whole German territory we are able to investigate whether the effect of local crime differs between urban and rural regions.

To test for heterogeneous responses to crime between urban and rural regions, we use information on both the territorial size and population density, where larger and less densely populated counties represent more rural areas. More precisely, we divide the sample into four quartiles according to both indicators and estimate the model separately for each quartile with results shown in Table 5.7.<sup>17</sup> The first column refers to the results from the unrestricted sample and serves as benchmark. Considering the results with respect to the territorial size, the estimated coefficients of violent crime are of comparable magnitude across the first three quartiles, but more than twice as large in the fourth quartile. Although large standard errors render most of the coefficient estimate insignificant, their absolute size is substantial and in line with the findings of the unrestricted sample. Assuming that counties of larger territorial size (Q3 and Q4) are predominantly rural counties, the results can be interpreted as a first indication that individuals living in such areas might be particularly sensitive to changes in local crime rates.

As shown in the last four columns of Table 5.7, this conjecture is substantially reinforced when using the population density instead of the territorial size to classify counties into urban and rural areas respectively. The coefficient estimates of violent crime are similar in magnitude across all quartiles except for the second quartile, which represents more rural areas. Compared with the other quartiles, it is clear that the effect of changes in crime rates is almost exclusively driven by the second population density quartile. Furthermore, we also find a considerable and statistically significant effect of both property and total crime rates on mental well-being for this quartile. Hence, these empirical findings provide support for the ‘resilience’ hypothesis, according to which individuals who are less exposed to crime become more sensitive to variations in crime rates. Together with the findings with respect to differences in socioeconomic characteristics these empirical results point towards a more complex relationship between actual crime rates, fear of crime and its effects on individual’s mental well-being (Pain, 2001).

<sup>17</sup>The different subsamples are not equally sized as the quartiles refer to number of county-year observations instead of person-year observations.

## 5.5 Conclusion

This article investigates whether variation in local crime rates affects the mental well-being of residents using rich nationally representative data for the whole German population. Linking local crime data to individual-level information on mental health from the German Socio-Economic Panel we find that a one standard deviation increase in local crime rates decreases individual mental well-being by about one percent (0.442 points on the MCS SF-12v2 scale) for violent crimes (corresponding to about one half of the impact of becoming unemployed), while weaker effects are found for property and total crime rates (one fourth and one seventh of the impact of unemployment, respectively). Using established QALY measures, we estimate the indirect psychological cost per violent crime to be around €16,800 or a total societal cost in excess of €9bn per year for Germany. These results are not sensitive to selective migration nor isolated to large urban areas, but are rather driven by less densely populated areas, suggesting that previous contributions might have underestimated the mental health effects from fear of crime. Furthermore, in contrast with much of the literature on perceived vulnerability to crime, our estimation results show that men, more educated and childless individuals react more to increases in violent crimes in their neighborhood. We conjecture that this finding might be explained by heterogeneous perceptions of actual victimization risks and coping strategies rather than differences in the perceived susceptibility of the consequences of and ability to control crime events.

To conclude, crime is a societal problem causing not only direct costs in terms of financial losses to direct victims of crime and upkeep of the criminal justice system, but also creates negative externalities to a potentially much larger population of individuals who are indirectly exposed and affected by crimes in their local neighborhoods. Fear of crime and victimization may lead to intangible costs in the form of behavioral and psychological responses which may greatly outweigh the direct and tangible costs among victims of crime. This paper confirms earlier findings that increases in crime rates induces significant mental stress of residents where crimes is on the rise, but furthermore also contribute with evidence that these effects vary along a number of dimensions; such as the social, geographical and demographic context. Such insights into the complexity of the relationship between crime levels, fear of crime and its psychological responses, necessitates for policymakers to customize more individualized responses to crime depending on the context at hand in order to achieve political goals of reducing the psychological impacts of crime. Indeed, on the question of the benefits of implementing focused victimization prevention programs in high crime areas, Taylor and Shumaker (1990) concludes that

“Participation in such efforts may be associated with people unhabituating to the threat profile; concern and fear may then increase; later on psychological distress may also increase [...] Programs such as Block Watch that may be useful in low crime areas may be extremely counterproductive in other high crime areas. Although police departments and other agencies may wish to push one program for all locations, such a strategy could be ineffective at best and potentially harmful at worst.” (pp. 637-638)

The results obtained in this study lend support to such an interpretation.



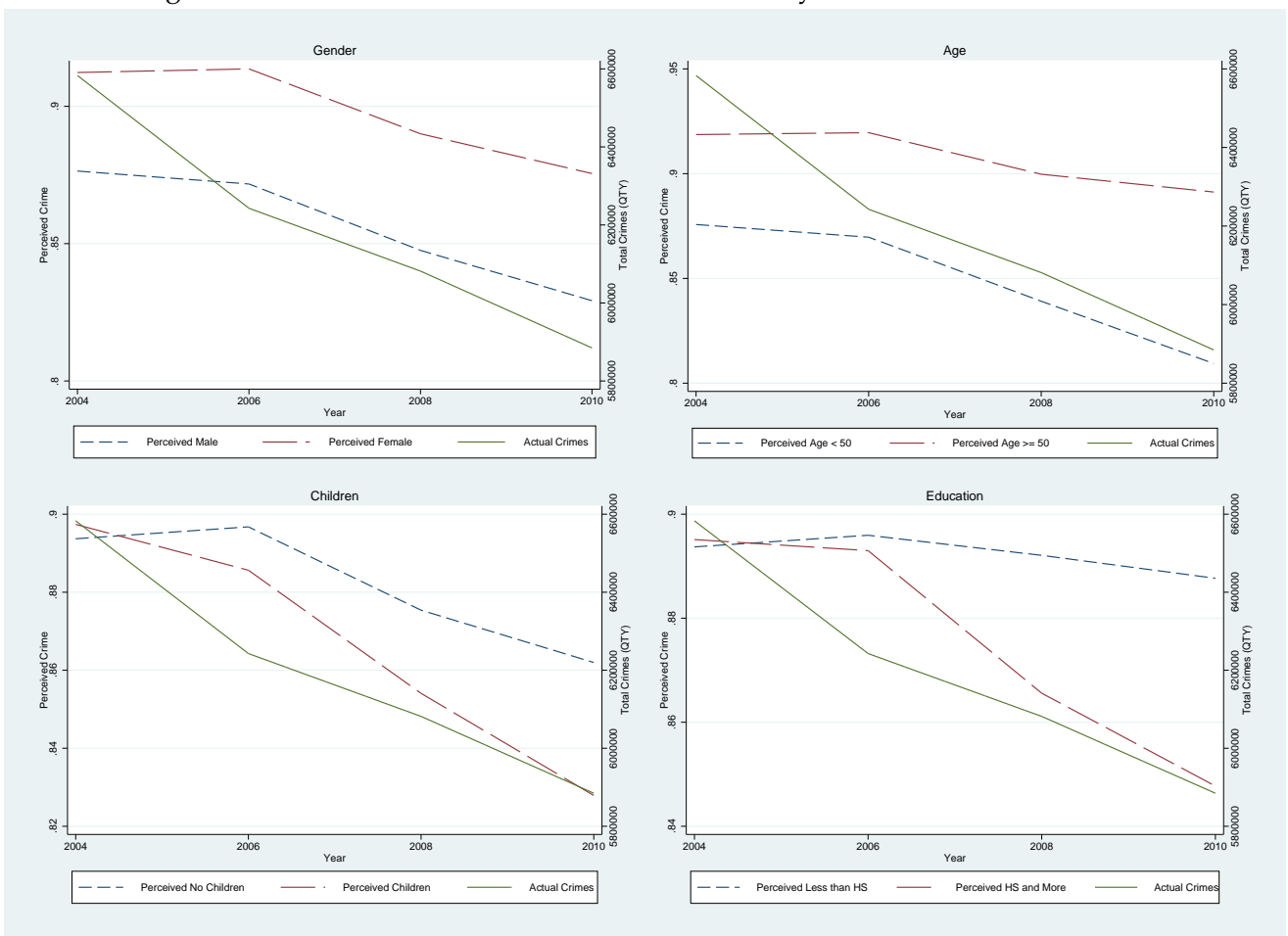
## 5.6 Appendix

Table 5.8: The Effect of Crime Rates on the Four Sub-scores of the MCS

|                | MCS<br>(1)          | SF<br>(2)         | VT<br>(3)         | RE<br>(4)         | MH<br>(5)         |
|----------------|---------------------|-------------------|-------------------|-------------------|-------------------|
| Total Crime    | -0.038<br>(0.155)   | -0.042<br>(0.190) | -0.037<br>(0.132) | 0.018<br>(0.184)  | -0.043<br>(0.124) |
| Violent Crime  | -1.453**<br>(0.730) | -0.990<br>(0.821) | -0.889<br>(0.719) | -0.597<br>(0.702) | -1.111<br>(0.719) |
| Property Crime | -0.332<br>(0.442)   | 0.084<br>(0.518)  | -0.380<br>(0.564) | 0.080<br>(0.429)  | -0.363<br>(0.443) |
| Time FE        |                     |                   | ✓                 |                   |                   |
| County FE      |                     |                   | ✓                 |                   |                   |
| Individual FE  |                     |                   | ✓                 |                   |                   |
| Controls       |                     |                   | ✓                 |                   |                   |
| Time trends    |                     |                   | ✓                 |                   |                   |
| # Observations |                     |                   | 72,362            |                   |                   |

Notes: Own calculations based on data from the SOEP and the PCS. Each cell shows the estimated coefficient, multiplied by 1000, of a separate regression. Altogether 15 regressions were performed. Columns (1) refer to the overall measure of mental-wellbeing (MCS) as the dependent variable. Columns (2) to (5) use the sub-scores social functioning (SF), vitality (VT), role emotional (RE), and mental health (ME) as dependent variable. Standard errors clustered at the county level are in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

Figure 5.2: Concerns about Crime vs Actual Crime by Individual Characteristics



Notes: Own calculations based on the SOEP and the PCS. The figure shows the number of actual crimes and the share of the population with at least some worries about crime in Germany separated by four socioeconomic characteristics.

## Chapter 6

# Concluding Remarks

Finding means to counteract the rising trend of HCE is an important issue for policymakers. Since main determinants of HCE are either hardly influencable in the short and medium run (demographic change) or not intended to be reduced at all (technological progress), it is necessary to find additional strategies to assess and control HCE also in the short and medium run. Two promising possibilities to influence HCE also in the short and medium run are increasing the efficiency of the health care system and reducing the prevalence of preventable risk factors. This thesis comprises four self-containing studies that address either efficiency aspects with respect to the German health insurance system or contribute to the understanding of how to reduce the prevalence of preventable individual and environmental risk factors. To answer the research questions under scrutiny, each of the chapters uses detailed individual-level data and applies appropriate micro-econometric techniques.

In chapter 2 we analyze switching behavior from SHI to PHI and provide robust empirical evidence that risk segmentation in favor of the PHI is present in the German health insurance system. This advantageous selection into the PHI may have two potential consequences: First, financial pressure on the SHI may further increase, as especially those who are generating positive marginal returns for the SHI have a higher likelihood to switch to the PHI. Second, in order to prevent individuals from leaving the SHI, sickness funds may adapt their offers to the needs of a relatively small share of potential switchers, which may not be in line with the needs of the majority of compulsory members. This, in turn, is likely to result in an inefficient allocation of the resources in the German health system. However, it is important to point out that most of the incentives to leave the SHI are attributable to the regulatory framework, which can be influenced by policymakers. Hence, creating regulatory conditions that focus more on competition between both systems may constitute a feasible strategy to increase efficiency.

A necessary precondition to increase efficiency of the German SHI market through fostering competition is that individuals are aware about differences between sickness funds and switch their current provider if they find a better option. Chapter 3 investigates the role of prices, supplemental benefits and service quality in the decision to switch sickness funds in the German SHI. The empirical results suggest that individuals are especially sensitive to differences in prices and that the provision of (non-essential) supplementary benefits and offering a high level of service quality seem to play – if at all – only a limited role in individuals sickness fund choices. Although we are not able to test for direct risk selection, we additionally find that the results are mostly insensitive to various subgroups of the

population, suggesting that differences in prices, supplementary benefits and service quality constitute no useful means of indirect risk selection of sickness funds. This is an important insight as it indicates that efficiency gains of more diversification and, hence, stronger competition, may outweigh the potential losses through indirect risk selection. However, conclusions should be made very carefully, as the results cannot be used to project individual and sickness fund behavior under less regulated conditions.

The empirical analysis conducted in chapter 4 aims at investigating if and how individuals adjust their health behavior as a consequence of new health information in the form of health problems. The reported results yield robust evidence that health problems affect individuals smoking behavior. More specifically, effects are strongest for those health problems that are most closely related to own health behavior, i.e. physical health problems. In contrast, accidents, which are usually not a consequence of individuals' health behavior, have virtually no impact on the decision to stop smoking. Hence, increasing individuals' risk perception through informing them about the harmful consequences of their own health behavior, for instance through shocking pictures on cigarette packages, seems to be an appropriate tool in reducing the prevalence of tobacco consumption. More importantly, this strategy is likely to be not restricted to smoking behavior but may also apply to other harmful health behaviors, such as alcohol consumption.

Chapter 5 analyzes how crime, as one example for preventable environmental risk factors, affects mental health of residents. Using variation in actual crime rates we estimate that local crime, in particular violent crime, significantly decreases individuals' mental well-being. As these spillover effects usually impact whole communities, indirect costs of crime are likely to amount to a substantial factor of total costs of crime, and potentially may even outweigh costs related to direct victimization. Moreover, we find that the overall effect is mainly driven by less densely populated areas. We also observe stronger effects for men, better educated on individuals without children are particularly sensitive to variation in crime rates. The insight that responses to crime vary along several dimensions emphasizes the complexity of the relationship between crime and its spillover effects and needs to be taken into account when designing strategies to reduce psychological impacts of crime.

This thesis provides relevant empirical findings which indicate that both increasing efficiency in the health insurance market and reducing the prevalence of preventable risk factors seem to constitute reasonable starting points in order to reduce HCE – also in the short and medium run. Yet, each study has also limitations, mostly due to data restrictions, and, hence, leaves room for future research. The analyses conducted in chapter 3, for instance, could be improved by exploiting administrative data from statutory sickness funds on both the sickness fund and individual level. More specifically, using detailed information about the influencable part of the benefit package for each sickness fund along with the possibility to follow switchers across sickness funds, for example using their never changing social security number (“Rentenversicherungsnummer”), would open up new possibilities that allow for an improved understanding of what drives individuals' sickness fund choice in the German SHI market. Although administrative data provide objective information on both individuals' health histories and their switching behavior, they lack on a large set of individual socioeconomic characteristics as well as personal attitudes and opinions, which make them less applicable in chapter 2 where we analyze the role of these factors in decision to switch health insurance systems. The empirical analysis of chapter 4 could be further improved by better information about the timing of the key events under scrutiny, i.e.

health events and smoking cessation, and by exploiting contemporaneously rather than retrospectively reported information on smoking behavior to account for potential smoking relapses. In addition, this analysis would benefit from more precise information about what causes the health problem and also from using information about consumption levels. Moreover, it would be interesting to investigate the effect of health information on other harmful health behavior, such as alcohol consumption or physical inactivity. With respect to chapter 5, it would be desirable to extend the present analysis to additional types of local crime. We were already able to collect detailed information on various crime categories for most of the 16 German federal states on county level. Yet we hesitate to use this data set, as we do not have access to the data of five federal states, most notably North Rhine-Westphalia and Bavaria. As the latter two federal states cover more than one third of the German counties, using the geographical restricted data set, which covers more crime categories, would mean losing a substantial part of the identifying within county variation. Apart from data on more crime categories, the analysis could be improved by having access to crime data on a more disaggregated level, for example on zip code level, as crime rates are likely to vary considerably within a county.

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