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ON CONSUMER PREFERENCES AND THE WILLINGNESS TO PAY FOR TERM LIFE INSURANCE

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On Consumer Preferences and the Willingness to Pay for Term Life Insurance

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Abstract

We run a choice-based conjoint (CBC) analysis for term life insurance on a sample of 2,017 German consumers using data from web-based experiments. To do so, we extend the traditional CBC approach by incorporating individual pricing factors such as age and health status to the experimental design. Individual-level part-worth utility profiles are estimated by means of a hierarchical Bayes model. Drawing on the elicited preference structures, we then compute relative attribute importances and different willingness to pay measures. In addition, we present comprehensive simulation results for a realistic competitive setting that allows us to assess product switching as well as market expansion effects. On average, brand, critical illness cover, and underwriting procedure turn out to be the most important nonprice product attributes. Hence, if a policy comprises their favored specifications, customers accept substantial markups in the monthly premium. Furthermore, preferences vary considerably across the sample. While some individuals are prepared to pay relatively high monthly premiums, a large fraction exhibits no willingness to pay for term life insurance at all, presumably due to the absence of a need for mortality risk coverage. We also illustrate that utility-oriented product optimization is well-suited to gain market shares, avoid competitive price pressure, and access additional profit potential. Finally, based on estimated demand sensitivities and a set of cost assumptions, it is shown that the traditional pricing approaches, which still prevail in the insurance industry, are clearly inferior to the preference-based methodology that we employ throughout this paper.

Keywords: Willingness to Pay, Term Life Insurance, Choice-Based Conjoint Analysis
JEL classification: C83; D12; G22

1 Introduction

Being able to adequately gauge consumer preferences and willingness to pay (WTP) is crucial for strategy formulation, product design, demand assessment, sales management, and, most notably, pricing decisions.[1] Accordingly, over the past decades, there has been substantial conceptual and methodological progress in the area of preference elicitation and WTP measurement. Unsurprisingly, the central determinants of consumer behavior are now well-understood for a broad range of goods and services. This development, however, seems to have bypassed the insurance sector, where prices are still largely set based on cost considerations. By the same token, there is a fairly limited amount of empirical research

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[1]The WTP or reservation price can be defined as the utmost amount of money that an individual is prepared to spend on a given good or service (see, e.g., Wertenbroch and Skiera, 2013). While some authors have suggested to view WTP as a range (see, e.g., Wang et al., 2007), we follow the more common conceptualization of treating it as a point estimate.

dealing with the question of how individuals actually evaluate risk transfer instruments.

In welfare theory, WTP is frequently employed to estimate the benefits of public health care systems (see, e.g., Johannesson, 1996; Hammitt and Graham, 1999; Olsen et al., 2004), safeguards against environmental hazards such as accidents, diseases, and disasters (see, e.g., Jones-Lee, 1974; Savage, 1993; Hammitt and Liu, 2004), as well as mortality risk mitigation (see, e.g., Shepard and Zeckhauser, 1984; Cropper and Sussman, 1988; Johannesson et al., 1997; Eeckhoudt and Hammitt, 2001; Alberini et al., 2006). Furthermore, there is a large strand of the development economics literature aimed at assessing the WTP for health coverage in rural areas across Africa (see, e.g., Asenso-Okyere et al., 1997; Dong et al., 2003; Ichoku et al., 2010), Asia (see, e.g., Asgary et al., 2004; Zhang et al., 2006; Chen et al., 2011), India (see, e.g., Mathiyazaghan, 1998; Dror et al., 2007), as well as Latin America (see, e.g., Vargas Bustamante et al., 2008; Eckhardt et al., 2011). Besides, preferences and WTP have been studied for crop insurance (Sherrick et al., 2003; Heenkenda, 2011), livestock insurance (see, e.g., Shaik et al., 2008; Buchenrieder and Fischer, 2009; Khan et al., 2013), flood insurance (Botzen and Van den Bergh, 2012), health insurance (Booske et al., 1999; Kerssens and Groenewegen, 2005; Van den Berg et al., 2008), long-term care insurance (Costa-Font and Font, 2009; Jacobs-Lawson et al., 2010), interest rate guarantees in unit-linked life insurance (Gatzert et al., 2011), weather insurance (Fraser, 1992; Musshoff et al., 2008), as well as auto, home, and household insurance (Hansen et al., 2013).

A thorough investigation of consumer preferences for term life insurance, however, has not been conducted to date. The only explicit figures in this regard come from a recent set of practitioner studies by Swiss Re (2012). Considering the product's importance in most developed economies, this is quite astonishing. In Germany, for example, the term life premium volume amounted to about EUR 3,145 million in 2012 with 7.48 million policies in force. However, sales peaked in 2006 and have been declining since with no signs of recovery. As a result, competition with regard to prices and contract design is intensifying. In this new market environment, insurance companies with a comprehensive understanding of consumer preferences will have a competitive advantage. The paper at hand is intended to substantiate this notion. We extend traditional choice-based conjoint (CBC) analysis, a powerful preference elicitation method grounded in random utility theory (RUT), and link respondents' individual risk factors such as age and health status to the experimental design. The hierarchical Bayes (HB) model underlying this approach allows us to estimate individual-level part-worth utility profiles from choice data that we collected through web-based experiments with 2,017 consumers in Germany. Based on the respective results, we then identify the most important product attributes from the customers' perspective, estimate WTP figures for incremental contract adjustments as well as complete term life policies, assess demand effects in a realistic competitive setting, and construct price-revenue as well as price-profit curves.

This manuscript is organized as follows. Section 2 begins with a brief review of CBC analysis and RUT. We then discuss the selection of product attributes and levels, describe the sample composition, outline the design of the discrete-choice experiments, explain the estimation routine for the part-worth utilities, and define key concepts such as relative attribute importances, WTP measures, and market simulations. Moreover, an extensive presentation of our empirical results can be found in Section 3. Finally, in Section 4, we summarize our main findings and conclude the paper.

2 Data and Methodology

2.1 Choice-Based Conjoint Analysis

Extant research in the insurance literature favored direct stated preference approaches such as the contingent valuation framework, in which customers are asked to explicitly specify their WTP via an open-ended question format (see Abrams, 1964; Mitchell and Carson, 1989). In the context of infrequently-purchased, durable, and rather abstract product categories that are associated with a more elaborate decision process, however, this method is known to generate inaccurate WTP estimates (see, e.g., Backhaus et al., 2005; Voelckner, 2006; Miller et al., 2011). Consequently, it is not suitable for insurance policies. Typical indirect stated preference methods come from the family of conjoint analyses, that found its way into the marketing literature about four decades ago (see Green and Rao, 1971; Johnson, 1974) and has since received considerable attention in academia and practice.[2] In particular, it has been regularly employed in WTP studies (see Breidert et al., 2006). Among the different conjoint preference elicitation tasks, CBC designs, in which consumers are required to select complete product profiles over sets of alternatives, are recommended for price-related research (see, e.g., Orme, 2009). This is due to the fact that, in contrast to ratings or rankings, choice tasks are cognitively less challenging, especially when the complexity of the marketplace is high. Apart from that, they more closely mirror the real purchase situation, in which the consumer is also confronted with a range of products (see, e.g., Huber, 1997).[3] Since each alternative shown in a given choice set is associated with distinct advantages and drawbacks, individuals are instigated to trade off product attributes against each other. Hence, through their selection, they convey preference information that can be employed for the estimation of part-worth utility profiles. In contrast to fast-moving consumer goods (FMCG) such as chocolate bars or soft drinks, however, the prices of life insurance products are directly related to individual risk factors. Thus, traditional CBC analysis based on uniform prices is unsuitable for such products. In order to overcome this issue, we incorporate these characteristics into our experiment and assign the respondents to ten different CBC analyses.

A frequently discussed limitation is the artificial nature of the choice tasks, which may give rise to hypothetical bias (see Cummings et al., 1995; Harrison and Rutström, 2008). To deal with this issue, some authors have proposed incentive-aligned CBC analyses, relying on the well-known Becker et al. (1964) mechanism that obliges participants to actually purchase the product under consideration, if their inferred WTP is higher than a randomly drawn purchase price (see Ding et al., 2005; Ding, 2007; Dong et al.,

[2] For an overview of common applications in market research refer to Green et al. (2001) or Gustafsson et al. (2003). Usage regarding insurance products is very limited to date, with a few exceptions relating to health insurance (Chakraborty et al., 1994; Kerssens and Groenewegen, 2005; Sricharoen and Buchenrieder, 2008; Van den Berg et al., 2008), livestock insurance (Buchenrieder and Fischer, 2009), crop insurance (Sherrick et al., 2003; Heenkenda, 2011), and value-added services in the insurance industry (Von Watzdorf and Skorna, 2010).

[3] As the WTP is a context-sensitive concept, the suitability of measurement methods critically hinges on their ability to emulate the actual evaluation process for the product under consideration.

2010). Yet, such purchase obligations are virtually infeasible for term life insurance contracts. Moreover, this issue should be negligible in the context of our study because even in the presence of hypothetical bias, the revealed demand effects commonly still lead to correct pricing decisions (see Miller et al., 2011). Thus, we refrained from adding an incentive alignment component to our CBC design.

2.2 Theoretical Foundations

CBC analysis is theoretically underpinned by RUT (see Thurstone, 1927; Von Neumann and Morgenstern, 1944). Let C denote the set of all relevant alternatives, y_i a discrete-choice variable for individual i, and M the total number of alternatives shown in a given choice task $c_i \subset C$. Each individual i associates alternative a with a latent utility U_{ia}. Under the assumption that all individuals are utility maximizers, alternative a is chosen (i.e., $y_i = a$), if and only if its utility exceeds that of all other available alternatives: $U_{ia} = \max(U_{i1}, U_{i2}, ..., U_{iM})$. To account for the probabilistic nature of choice, RUT describes utilities by means of a deterministic component V_{ia} and a stochastic component ϵ_{ia}, which captures unobserved aspects as well as measurement error (see, e.g., Train, 2009):

$$U_{ia} = V_{ia} + \epsilon_{ia}. \tag{1}$$

The condition under which a is selected can then be expressed as follows:

$$\begin{aligned} U_{ia} &> U_{im} \\ V_{ia} + \epsilon_{ia} &> V_{im} + \epsilon_{im} \\ \epsilon_{ia} - \epsilon_{im} &> V_{im} - V_{ia} \qquad \forall \ m \neq a. \end{aligned} \tag{2}$$

Therefore, the probability of individual i choosing alternative a equals

$$\Pr(y_i = a) = \Pr(U_{ia} > U_{im}) = \Pr(\epsilon_{ia} - \epsilon_{im} > V_{im} - V_{ia}) = 1 - \Pr(\epsilon_{ia} - \epsilon_{im} \leq V_{im} - V_{ia}). \tag{3}$$

By assuming that the ϵ are independent and adhere to a Gumbel (type-I extreme value) distribution, it is possible to derive the Lucean choice model (see, e.g., McFadden, 1974),

$$\Pr(y_i = a) = \frac{\exp(V_{ia})}{\sum_{m=1}^{|C|} \exp(V_{im})}, \tag{4}$$

which is characterized by the independence from irrelevant alternatives (IIA) property.[4] We may now condition on the choice task c_i and explicitly specify V_{ia} and the V_{im} in terms of product attributes to derive the multinomial logit (MNL) model that lies at the heart of the CBC approach:

$$\Pr(y_i = a|c_i) = \frac{\exp(\mathbf{x}_a \boldsymbol{\beta}_i)}{\sum_{m=1}^{M} \exp(\mathbf{x}_m \boldsymbol{\beta}_i)}. \tag{5}$$

[4]IIA implies that "the odds of choosing alternative a in relation to alternative b must be constant, regardless of what other alternatives are present" (Louviere and Woodworth, 1983).

Here, the $\mathbf{x}$ are row vectors that include the Q predictors for the characteristics (attribute levels) of the alternatives that appear in choice task c_i and $\boldsymbol{\beta}_i = (\beta_{i1}, ..., \beta_{iQ})'$ represents the column vector of unknown individual-level parameters (part-worth utilities).[5]

2.3 Product Attributes and Levels

There is no generally accepted approach for the determination of appropriate product attributes and levels to be used in a CBC research design. We decided to conduct focus group discussions with industry professionals from Swiss Re, based on which we adopted the six attributes (i) insurance premium, (ii) term assured, (iii) sales channel, (iv) underwriting procedure, (v) brand, and (vi) critical illness (CI) rider. The sums insured for the policies were held fixed at EUR 100,000. When specifying the corresponding levels, we adhered to the guidelines suggested by Orme (2002), particularly concise labeling, independence, and mutual exclusivity. An overview of all attributes and levels can be found in Table 1.

Selecting levels for the monthly insurance premium was a particularly challenging task. First of all, we aimed to avoid distortions due to the range and number-of-levels effects (see Verlegh et al., 2002). Thus, as suggested in the extant literature, we determined a realistic range bounded by the minimum and maximum price of comparable policies offered in Germany (see, e.g., Miller et al., 2011). This was achieved by interviewing market experts and evaluating quotes for a large number of products from the online comparison platform www.check24.de. Apart from that, term life insurance differs from common consumer goods in that there is a direct link between the individual's age and physical condition on the one hand, and the product's costs on the other hand. More specifically, fair premiums for old policyholders with impaired health are substantially higher than for young and fit ones. Accordingly, we needed to ensure that each individual is confronted with a price range that matches his or her mortality risk. For this purpose, we allocated the survey participants to ten different groups that were characterized by an age bracket and a smoking status. Throughout the choice experiments, each of those groups saw product profiles based on the corresponding price levels ("very low" to "very high") as shown in Table 2. Moreover, we offered policies with 10, 15, or 20 year terms that could be purchased online or face-to-face from a salesperson. With regard to the underwriting procedure, we allowed for questionnaires with three and ten questions, an innovative twelve-month waiting period until the coverage becomes effective, as well as the traditional full-fledged medical examination. The brand of the contract provider was represented by three major categories: large insurers with a well-known brand (Allianz, Axa, Debeka, Hannoversche, R+V), lesser-known insurers with a rather insignificant footprint in the German market (Cardif, Heidelberger Leben, Itzehoer, Mecklenburgische, MyLife), and companies with a strong brand name that is not associated with insurance (Aldi, Amazon, Apple, IKEA, Volkswagen). Finally, the CI rider is an innovative feature that entitles the policyholder (not the beneficiary) to a lump sum payment if he is diagnosed with a severe disease (e.g., cancer) as defined in the contract's terms and conditions.

[5] Note that, in contrast to conditional logit models, MNL predictors are usually respondent characteristics rather than product attributes, whereas the coefficients vary across alternatives instead of individuals (see, e.g., McFadden, 1986).

No.	Attribute	Levels	Comment
1	Insurance Premium	5 levels from "Very Low" to "Very High" Equally sized price steps	EUR amounts differ by group (see Table 2) Source: market quotes/expert opinion
2	Term Assured	10, 15, 20 Years	-
3	Sales Channel	Personal, Online	-
4	Underwriting Procedure	Questionnaire (3), Questionnaire (10), 1-Year Survival, Medical Examination	-
5	Brand	Brand Insurer, Lesser-Known Insurer, Noninsurance Brand	Graphical representation (logos) within the stimuli
6	CI Rider	Yes, No	EUR 50,000 benefit if diagnosed with a severe disease (death benefit unaffected)
-	Sum Insured	Fixed at EUR 100,000	Participants were informed that additional coverage would be available

Table 1: Attributes and Levels for the CBC Analysis

Nonsmoker	Price Levels (EUR)				
Age	Very Low	Low	Medium	High	Very High
20-29	3.00	6.00	9.00	12.00	15.00
30-39	5.00	10.00	15.00	20.00	25.00
40-44	7.00	14.00	21.00	28.00	35.00
45-49	10.00	20.00	30.00	40.00	50.00
50-54	20.00	40.00	60.00	80.00	100.00

Smoker	Price Levels (EUR)				
Age	Very Low	Low	Medium	High	Very High
20-29	5.00	8.75	12.50	16.25	20.00
30-39	10.00	17.50	25.00	32.50	40.00
40-44	20.00	35.00	50.00	65.00	80.00
45-49	30.00	52.50	75.00	97.50	120.00
50-54	60.00	105.00	150.00	195.00	240.00

Table 2: Levels of the Attribute Premium (in EUR) for the Ten Mortality Risk Groups

2.4 Sample Selection and Discrete-Choice Experiments

We collected data for a sample of 2,017 German consumers who identified themselves as insurance decision makers.[6] All participants were between 20 and 54 years old and population-representative with regard to domicile state and gender. In addition, half of them actually own a term life insurance contract. As discussed in the previous section, respondents were allocated to ten groups according to their stated age and smoking habits. To enhance estimation quality, a roughly equal distribution across groups was targeted by means of a ten percent quota and met up to a maximum error margin of 0.8 percentage points. We established contact with the individuals through the consumer panel of a well-respected market research firm, seeking to maximize response rates and minimize the amount of missing data. Participation in the study was incentivized by bonus points that can be spent for consumption purposes.

The online survey relied on the latest CBC system of Sawtooth Software, Inc. and underwent a technical pretest before the two-week field phase. At the outset, we asked for completion of categorization questions with regard to age, gender, smoking habits, and domicile state. This introductory part was followed by the choice experiments. After a short explanation of the hypothetical buying situation, the mechanics of term life insurance, as well as the product attributes, participants were confronted with twelve choice tasks, each of which comprised two complete policy profiles and the possibility to opt out of the purchase (none option). While the attribute order within each conjoint stimulus remained fixed, the pairwise comparisons were generated according to the balanced overlap method. The latter is a randomized experimental design that accounts for the principles of minimal overlap, level balance, as well as orthogonality and thus curtails psychological context and order effects (see Sawtooth Software, 2013).[7] As recommended by Orme (2002), we refrained from prohibiting any attribute level combinations to avoid estimation problems and confounded utilities. At the end of the survey, we included a set of additional questions to capture basic socioeconomic information about the respondents.

2.5 Estimation of Individual-Level Part-Worth Utility Profiles

We estimated part-worth utilities from the observed choices by means of the HB routine implemented in Sawtooth CBC/HB 5.0 (see Sawtooth Software, 2009).[8] The corresponding set-up is hierarchical in the sense that it comprises two levels. On the individual or lower level, the choice data is explained by the MNL model in Equation (5). In addition, there is an aggregate or upper level comprising the prior for the individual-level part-worth utilities. More specifically, the $\boldsymbol{\beta}_i$ in Equation (5) are assumed to come from a multivariate normal distribution with mean vector $\boldsymbol{\alpha}$ and covariance matrix $\mathbf{D}$ that describes the heterogeneity across respondents. For computational ease, the HB approach relies on another multivari-

[6]In the context of this study, "insurance decision makers" are defined as persons, who either purchase insurance policies themselves or participate in the decision to do so. This criterion was applied to ensure that respondents understand the product type under consideration and can therefore make sufficiently informed decisions between the conjoint stimuli. Robustness of the results was confirmed with a purely population-representative sample comprising another 938 individuals.

[7]The reader is referred to Huber and Zwerina (1996) for a more detailed description of these conjoint design principles.

[8]The suitability of HB models for conjoint studies has been documented in several pieces of high-class research (see, e.g., Arora et al., 1995; Lenk et al., 1996; Arora et al., 1998; Huber, 1998; Arora and Huber, 2001; Train, 2009).

ate normal and the inverse Wishart distribution as conjugate hyperpriors for $\boldsymbol{\alpha}$ and $\mathbf{D}$.

The software runs a robust iterative process with initial values of zero to estimate the unknown parameters. The Metropolis-Hastings Algorithm is employed to draw the $\boldsymbol{\beta}_i$, while $\boldsymbol{\alpha}$ and $\mathbf{D}$ are determined by means of Gibbs sampling.[9] An important property of the HB model is the incorporation of shrinkage, implying that the individual-level estimates become more efficient, because they inform each other via the upper level. We ran 20,000 burn-in iterations of the Markov chain and 50,000 post-convergence iterations for the subsequent sampling of the posterior distributions. After the Bayesian updating of the prior distribution with our choice data was complete, we imposed monotonicity constraints on the posterior part-worth utilities for the attribute premium using the tying after estimation procedure.[10] The reason is that monotonically falling price-utility curves are a necessary condition for the computation of the maximum WTP measure that will be introduced in the next section.

2.6 Relative Importance, Willingness to Pay, and Shares of Preference

The MNL model in Equation (5) is unidentified. Thus, to find a unique set of estimates, one needs to impose some form of restriction on the parameters. CBC analysis commonly relies on a normalizing constraint for identification such that the sum of part-worth utilities equals zero. This is achieved through effects coding of the product attributes.[11] As a corollary, conjoint utilities are interval scaled, i.e., they do not exhibit a meaningful origin (see, e.g., Orme, 2010). For this reason, we may add any arbitrary constant to the part-worth profile of each product attribute without affecting the predicted choice probabilities. On the other hand, utilities are not comparable across attributes and ratios must not be formed.[12]

Since a direct interpretation of the part-worth utility profiles is complicated by their interval-scale character, they will be employed to derive metrics with a more intuitive economic meaning. We begin with relative importance, which measures the impact of an attribute on the overall utility of a product in percentage terms (see Orme, 2010). Formally, the relative importance RI_{ik} of attribute $k \in \{1, 2, 3, 4, 5, 6\}$ (see Table 1) with levels $l \in \{1, ..., L_k\}$ as perceived by individual i can be expressed as follows:

$$\mathrm{RI}_{ik} = \frac{\max\limits_{l}(\beta_{ikl}) - \min\limits_{l}(\beta_{ikl})}{\sum_{k=1}^{6}\left(\max\limits_{l}(\beta_{ikl}) - \min\limits_{l}(\beta_{ikl})\right)}. \tag{6}$$

The RI_{ik} follow a ratio scale, add up to 100 percent for each respondent i, and are readily comprehensible: the larger the utility range of an attribute, the higher its potential to increase or decrease an individual's choice probability for a product. Therefore, based on the RI_{ik}, one may identify key product

[9] Technical details on these Markov Chain Monte Carlo (MCMC) methods can be found in Chib and Greenberg (1995).

[10] After an unconstrained HB estimation, the utility values of each offending pair are repeatedly tied until all violations have been eliminated. This method performs well in terms of hit rates and share predictions (see Johnson, 2000).

[11] More specifically, the last level of every attribute is estimated as the negative of the sum of the other levels. Although dummy coding would also introduce an identification constraint by selecting one attribute level as the baseline category and setting it to zero, effects coding has emerged as the standard in the early 1990s (see Sawtooth Software, 2009).

[12] Furthermore, estimates from samples with different variances are not directly comparable (see Swait and Louviere, 1993).

features for a given market.[13]

Beyond relative importances, our main focus lies on measures for the WTP, which also facilitate comparisons (see, e.g., Jedidi and Zhang, 2002). We differentiate between the marginal WTP for changes in attribute levels and the maximum WTP for whole products. A common approach to estimate individual i's marginal WTP for the step from level l to level h of product attribute k ($\neq 1$), is based on a simple exchange-rate between utility and price (see, e.g., Jedidi and Jagpal, 2009):

$$\text{margWTP}_{ik}(h,l) = \left(\frac{\max(p_i) - \min(p_i)}{\max\limits_{l}(\beta_{i1l}) - \min\limits_{l}(\beta_{i1l})} \right) \cdot (\beta_{ikh} - \beta_{ikl}), \tag{7}$$

where p_i denotes the levels of the price attribute ($k = 1$) in EUR associated with age and smoking status of individual i (see Table 2) and the β_{i1l} represent the corresponding part-worth utilities. margWTP_{ik} incorporates the marginal rate of substitution between nonprice and price attribute and expresses the utility increases or decreases induced by product adjustments in monetary terms. The resulting figures, however, should be interpreted with care, because this concept assumes a strictly linear part-worth curve across the whole price range, does not consider a specific product context, and neither takes into account the possibility to opt out of the purchase nor the impact of competition in the market.[14]

With regard to the maximum WTP for whole products, we adopt the approach of Kohli and Mahajan (1991), who suggest a definition based on the following relationship:

$$u_{i|\sim p} + v_i(p_i) \geq u_i^* + \xi, \tag{8}$$

where $u_{i|\sim p}$ equals the sum of utilities for all product attributes except price as perceived by individual i, $v_i(p_i)$ is the utility associated with price level p_i, u_i^* represents a threshold utility, and ξ stands for an infinitesimally small positive number. Following Jedidi and Zhang (2002), we treat u_i^* as the utility of the none option, implying that individual i will only choose the product, if the associated total utility is at least as high as the utility of not buying. The maximum WTP can now be derived by finding the highest price for which Equation (8) still holds (indifference condition):

$$\text{maxWTP}_i = v_i^{-1}(u_i^* - u_{i|\sim p}), \tag{9}$$

with v_i^{-1} denoting the inverse of the price-utility curve.[15] We employ a piecewise-linear approach to calculate the maximum WTP (see, e.g., Miller et al., 2011): since the participants' part-worth profiles for the insurance premium have been captured at discrete points only, they are interpolated with straight lines. Similarly, in case the values fall outside the range covered by our estimates, the nearest segment

[13] Due to statistical noise, conjoint part-worth profiles will almost never be flat. Hence, the RI_{ik}-values for attributes with little relevance may be slightly upward biased, because of their focus on the extreme utility values (see Orme, 2010).

[14] Beside these conceptual limitations, it may yield heavy-tailed posterior distributions (see, e.g., Sonnier et al., 2007).

[15] Jedidi and Jagpal (2009) differentiate between an informational and an allocative effect of price and document that WTP estimates can become negative, when the two are not separated within a CBC analysis. To mitigate this problem, we followed Rao and Sattler (2003) by exclusively adopting the most prominent product attributes.

of the curve is extrapolated.

We will complete the analysis with a comprehensive simulation of consumer behavior in a competitive environment consisting of four concrete term life products. Demand in this hypothetical market will be predicted by the first choice method (maximum utility rule), which assumes that each individual buys the policy with the highest overall utility (see Orme, 2010). Thus, we are able to convert our individual-level part-worth profiles into shares of preference (shares of choice). Shares of preference are an even more intuitive measure than classical WTP and, given suitable conditions, may track actual long-term equilibrium market shares quite well.[16] By modifying contract features and varying prices, it is then possible to assess product switching as well as market expansion effects. Finally, we add a set of cost assumptions and derive price-profit curves for the providers of the four term life insurance policies.

3 Empirical Results

3.1 Part-Worth Utilities

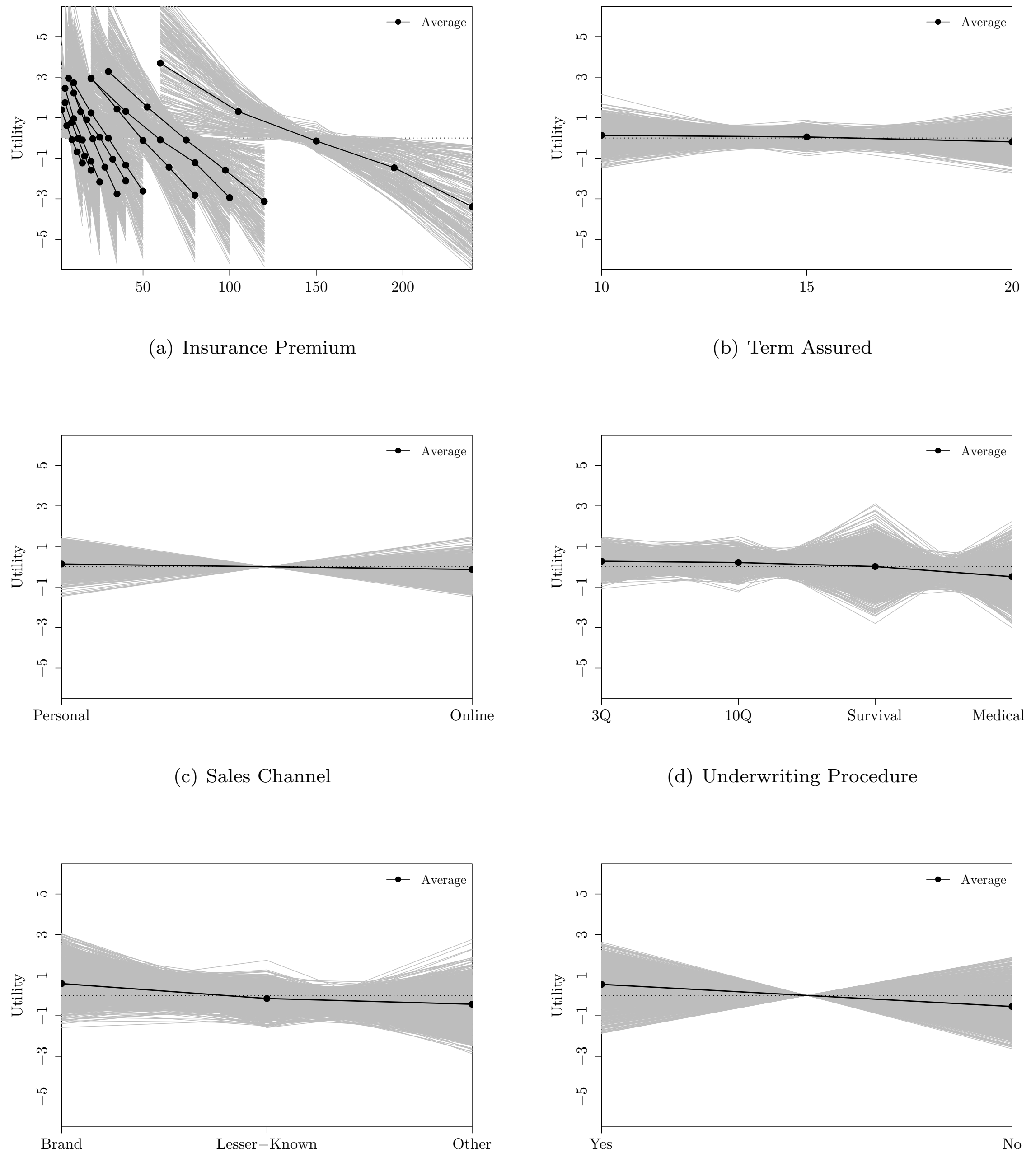
From the participants of the discrete-choice experiments, we removed those with answer times below one minute and WTP estimates above EUR 1,000. As a result, we were left with a sample of 1,995 consumers.[17] Figure 1 shows their individual-level part-worth profiles for the six attributes in our CBC analysis as gray lines. The horizontal axis and the vertical axis represent the attribute levels and the corresponding utility values, respectively. This preference information forms the basis for all further results. To facilitate the interpretation, we have highlighted the aggregate-level part-worth profiles (average participant) by bold black lines. Across all 1,995 individuals, we obtain a mean root likelihood (RLH) of 0.759, which is approximately 2.3 times better than chance.[18]

In Figure 1(a), we have summarized the price-utility curves for all ten mortality risk groups. The 20 to 29 year old nonsmokers, which were confronted with the lowest premium levels in the discrete-choice experiments, are located on the very left, while the 50 to 54 year old smokers can be found at the right end of the graph. At first glance, we notice that the black lines in this subfigure are substantially steeper than those for the remaining product attributes, indicating that, in the aggregate sample, the monthly premium contributes the largest amount of utility to a term life policy. Furthermore, consider the part-worth profiles in Figure 1(b). Although some of the individuals clearly prefer shorter over longer terms assured and vice versa, the flat shape of the black line indicates that the average respondent is virtually indifferent with regard to this attribute. The same is true for the sales channel, as shown in Figure 1(c), which also exhibits almost identically-distributed preferences across its two levels. Figures 1(d), (e), and (f), in contrast, reveal a clear tendency: the average consumer derives the highest utilities from

[16] Yet, as conjoint part-worth profiles do not incorporate many important real-world determinants such as advertising, promotions, and sales force effects, one should be careful not to confound these two concepts (see Orme, 2010).

[17] The mean response time for the discrete-choice experiments among the remaining participants amounts to 8.27 minutes.

[18] The root likelihood measures the goodness of fit for the individual-level part-worth profiles (see, e.g., Sawtooth Software, 2009, 2013). Given M alternatives per choice task, the minimum value of the RLH is $1/M$, which resembles a so-called chance model with equal probabilities for each $m \subset M$, while the best possible value is 1.0.



(a) Insurance Premium

(b) Term Assured

(c) Sales Channel

(d) Underwriting Procedure

(e) Brand

(f) Critical Illness Cover

Figure 1: Individual-Level Part-Worth Utility Profiles

This figure summarizes the individual-level (gray lines) and aggregate-level (black lines) part-worth utility profiles for all six attributes in the CBC analysis. This preference information forms the basis for all further results.

policies that are underwritten based on a brief (three-item) questionnaire, offered by well-known insurance companies, and provided with a CI rider. The negative slope of the respective part-worth profiles implies that the other levels of the attributes underwriting procedure, brand, and critical illness cover are less desired. However, it should be noted that there is a relatively large variation around the aggregate-level utility values of the one-year survival option, the full medical examination, the noninsurance brand, and the critical illness cover. Hence, in these cases, consumer preferences seem to be quite heterogeneous.

3.2 Relative Attribute Importances

Based on the individual-level part-worth profiles, it is possible to compute the relative importance of each product attribute for the 1,995 consumers in our sample. Figure 2 shows the corresponding posterior distributions together with their means as well as the upper and lower bounds of the 95 percent highest density interval (HDI). As can be seen in subfigure (a), the insurance premium exhibits an aggregate-level relative importance of approximately 41.38 percent and is therefore the key feature of a term life policy. To put it differently, price increases or reductions trigger the largest utility changes for the average respondent. Due to the rather unemotional and standardized nature of the product, this is not surprising. Interestingly, however, the associated distribution across individuals appears relatively symmetric and entails a wide HDI, ranging from a relative importance of merely 3.09 up to 75.27 percent. Thus, there are also numerous respondents with low price sensitivities. Furthermore, turning to subfigures (b) and (c), we notice that the term assured and the sales channel exhibit aggregate-level importances of 7.86 and 6.66 percent, respectively. Apart from being the least relevant attributes for the average consumer, they also involve the lowest preference heterogeneity: 95 percent of the probability mass lies in the comparatively narrow interval between a relative importance of approximately 0 and 20 percent. Finally, in subfigures (d), (e), and (f), we find notable aggregate-level importances for the brand (15.89 percent), the underwriting procedure (14.78 percent), and the CI cover (13.44 percent). Therefore, these three nonprice attributes are potential levers for product design that might help insurers to avoid pure price competition. Similar to the monthly premium, however, the wider HDIs indicate a nonnegligible degree of disagreement among the respondents.

3.3 Marginal Willingness to Pay for Changes in Attribute Levels

The marginal WTP expresses utility increases or decreases associated with changes in attribute levels in monetary terms. We examine it by means of incremental moves from right to left along the x-axis of the part-worth profiles in Figure 1, i.e., we focus on one-step adjustments that are perceived as improvements by the average consumer and thus increase his WTP. Modifications in the opposite direction would lead to an equivalent WTP reduction. To facilitate the interpretation, we have sorted the posterior distributions for the marginal WTPs in descending order of their means. Accordingly, Figure 3 (Figure 4) shows the results for those four attribute level changes that lead to the highest (lowest) aggregate-level WTP additions. The only distribution that we do not report is the one for a shortening of the underwriting questionnaire from ten to three items. Its mean marginal WTP of merely EUR 0.34 is negligible.

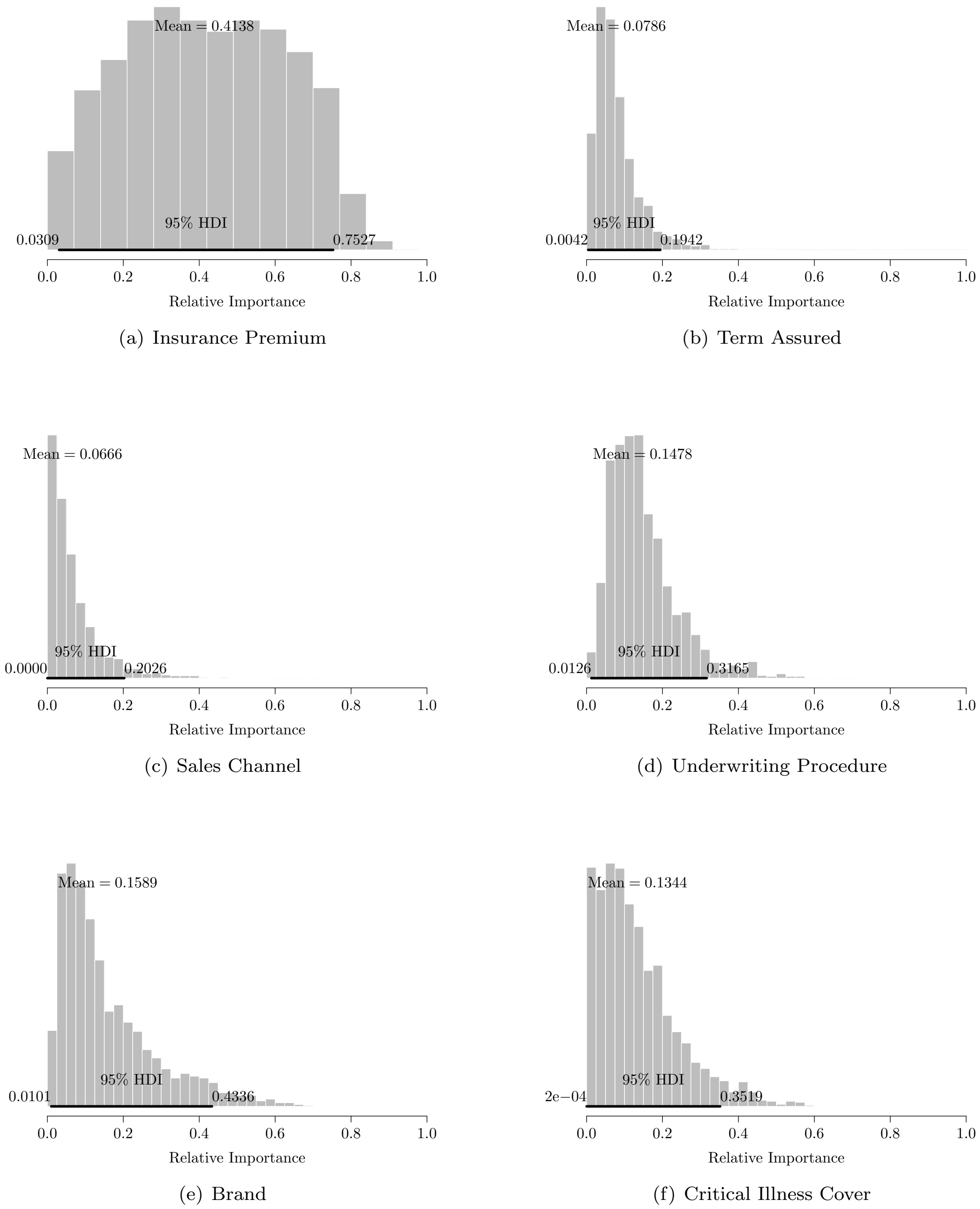
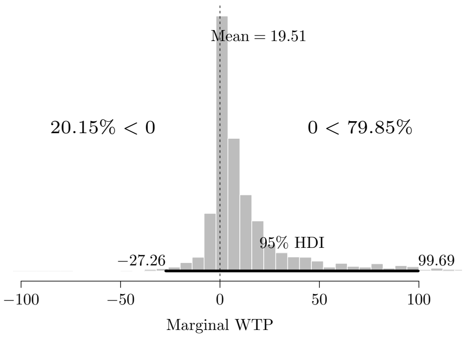
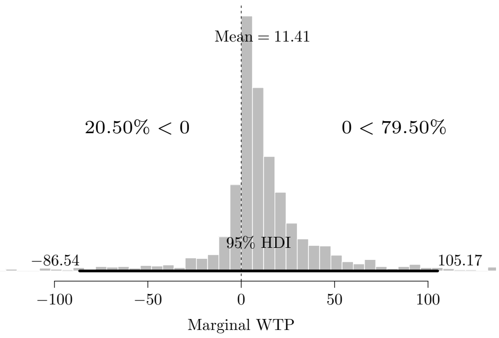


Figure 2: Relative Attribute Importances

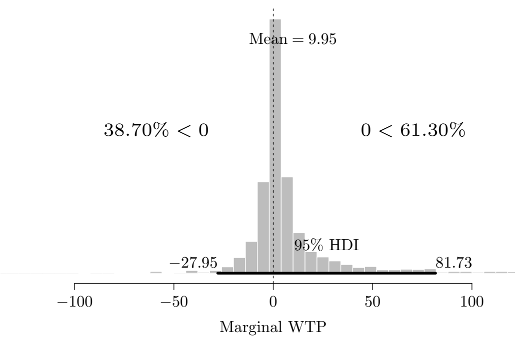
This figure shows the distributions of the individual-level relative importances for all six attributes across the 1,995 individuals in the sample, including means (aggregate-level values) and 95 percent highest density intervals.



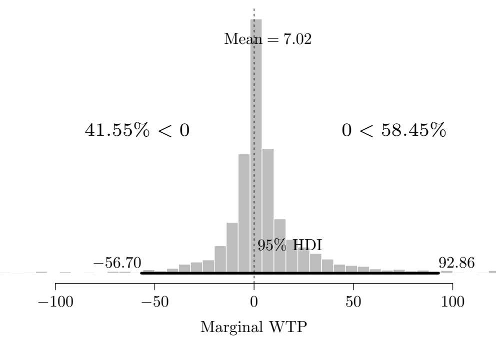
(a) From Lesser-Known Insurer to Brand Insurer



(b) From no CI Cover to CI Cover



(c) From Online to Personal

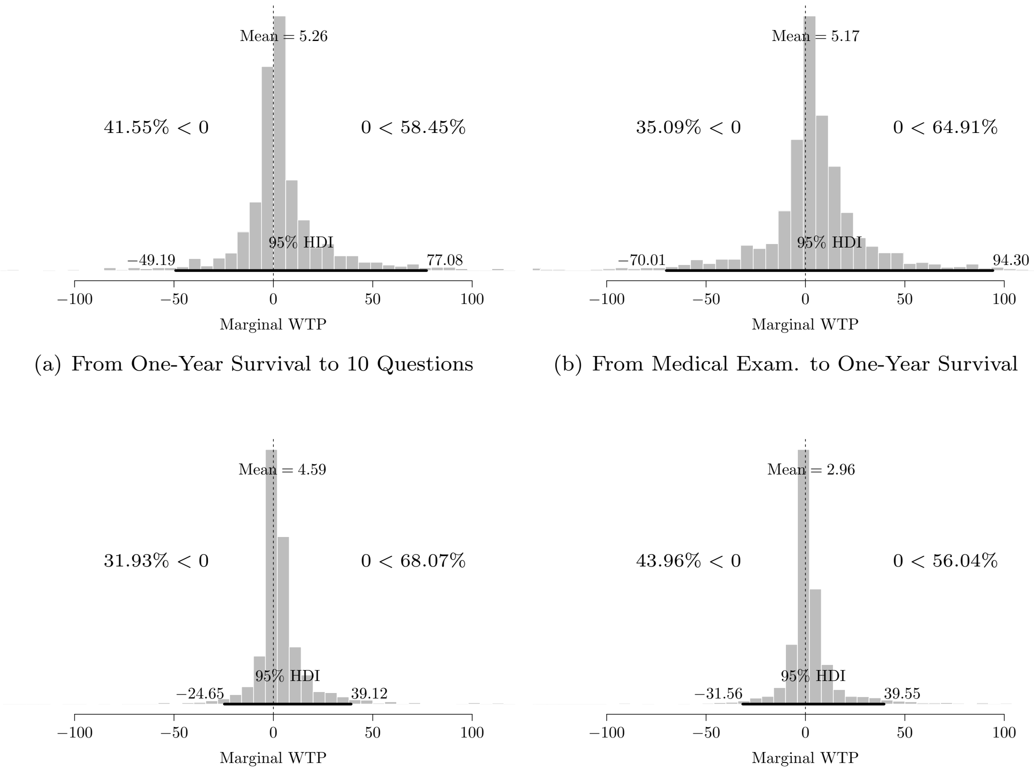


(d) From Noninsurance Brand to Lesser-Known Insurer

Figure 3: Marginal Willingness to Pay for Changes in Attribute Levels I

This figure shows the distributions of the individual-level marginal willingness to pay for different changes in attribute levels with means and 95 percent highest density intervals.

In Figure 3(a) we see that, on average, people are prepared to pay a markup of EUR 19.51 if the term life policy is offered by a well-known instead of a lesser-known insurance company. Although there is a considerable variation on the individual level, about 80 percent of the consumers exhibit a positive marginal WTP. The same is true for the addition of a CI cover as shown in Figure 3(b), which, however, is associated with a lower mean of EUR 11.41 and a wider 95 percent HDI, particularly in the left tail. The latter implies that some respondents are prepared to pay much less for a contract if this feature is included. Moreover, Figures 3(c) and (d) display the marginal WTP distributions for the switch from online to personal sale and from a noninsurance brand to a lesser-known insurance company. The respective aggregate-level values of EUR 9.95 and EUR 7.02 as well as the fact that around 60 percent of the probability mass lies in the positive area indicate that a majority of consumers considers these to be valuable attribute level changes.



(a) From One-Year Survival to 10 Questions (b) From Medical Exam. to One-Year Survival

(c) From 20 to 15 Years (d) From 15 to 10 Years

Figure 4: Marginal Willingness to Pay for Changes in Attribute Levels II
This figure shows the distributions of the individual-level marginal willingness to pay for different changes in attribute levels with means and 95 percent highest density intervals.

Next, we examine an adjustment of the underwriting procedure from the one-year survival condition to a ten-item questionnaire. The respective results can be found in Figure 4(a). We estimate a mean marginal WTP of EUR 5.26 and 58.45 percent of the individuals are willing to accept a price increase for this attribute modification. Similarly, from Figure 4(b) we learn that the shift from a medical examination to the one-year survival condition is worth EUR 5.17 to the average consumer. The corresponding fraction of respondents with a positive marginal WTP amounts to 64.91 percent. Finally, Figures 4(c) and (d) contain the distributions for a shortening of the term assured from 20 to 15 and from 15 to 10 years. For these changes, we obtain the smallest aggregate-level marginal WTPs of EUR 4.59 and EUR 2.96 but also the narrowest HDIs. In the first case, almost 70 percent of the individual-level results are greater than zero. Despite the comparatively smaller distribution means, this is an important insight for insurance companies, since policies with shorter terms assured can be offered at a lower cost. At the same time, however, most customers seem to be willing to pay higher premiums for them.

Overall, the heterogeneity of preferences that we documented based on the part-worth profiles and relative importances feeds through into the marginal WTPs. Taking into account that the latter are additive across the full range of possible adjustments, it becomes clear that the three attributes with the highest aggregate-level marginal WTPs, namely brand (EUR 26.53), CI cover (EUR 11.41), and underwriting procedure (EUR 10.77), are also those that were found to be most important for the average consumer in the sample.

3.4 Maximum Willingness to Pay for Complete Products

The concept of maximum WTP is linked to concrete products. More specifically, as discussed in Section 2, we are searching for the single price, which makes the consumer indifferent between buying and not buying the policy under consideration. Hence, we worked together with industry experts from the global reinsurer Swiss Re in order to define a set of four generic term life insurance contracts that represents a realistic snapshot of both current and potential future offerings in the German market. An overview of these products, which will form the basis for the remaining analyses, is provided in Table 3. All four of them exhibit a term assured of 15 years and a death benefit of EUR 100,000. The "budget" product has been designed as a cost-efficient alternative. It is sold online, underwritten based on a ten-item questionnaire, provided by a noninsurance company, and does not comprise a CI rider. Furthermore, we have a "classic" product, mimicking the traditional type of term life insurance sold in Germany. This policy can be purchased from a salesperson, involves a full medical examination, is offered by a well-known insurance company, and lacks the CI option. The two remaining offerings will be called "innovative" and "premium" product. Being sold online by a lesser-known insurance company with the one-year survival condition and the CI cover, the former emphasizes rather modern contract features. The latter, in contrast, comprises that particular level of each attribute (apart from the term assured) from which the average consumer derives the highest utility (see Figure 1). Accordingly, it is distributed face-to-face, relies on a three-item questionnaire, originates from a well-known insurance company, and includes the CI feature.

Figure 5 contains the distribution of the maximum WTP for each aforementioned product. We observe a clear order in the aggregate-level results as well as the width of the 95 percent HDI. As could be expected, the average respondent would pay the lowest monthly premium for the budget policy (EUR 17.63), followed by the classic (EUR 21.26) and innovative products (EUR 24.80). Due to the fact that it comprises the most desirable features, the premium term life contract exhibits the WTP distribution with the highest mean (EUR 34.76). Similarly, its 95 percent HDI extends furthest into the right tail (EUR 150.76), implying that, compared to the other products, there is a larger number of consumers with very high WTP values. Moreover, we again document a considerable variation on the individual level, which arises due to the heterogeneity of preferences documented above. Finally, all four distributions show a dominant peak around zero which indicates that between 45 percent (premium

Budget Product	
Term Assured	15 years
Sales Channel	Online
Underwriting	10 questions
Brand	Noninsurance brand
CI Cover	No

Classic Product	
Term Assured	15 years
Sales Channel	Personal
Underwriting	Medical examination
Brand	Well-known insurer
CI Cover	No

Innovative Product	
Term Assured	15 years
Sales Channel	Online
Underwriting	1-year survival
Brand	Lesser-known insurer
CI Cover	Yes

Premium Product	
Term Assured	15 years
Sales Channel	Personal
Underwriting	3 questions
Brand	Well-known insurer
CI Cover	Yes

Table 3: Reference Term Life Products

This table summarizes the specifications (attribute levels) of the four generic term life products that form the basis for all remaining analyses. Each policy exhibits a sum assured of EUR 100,000.

product) and 65 percent (budget product) of the respondents do not have a noteworthy WTP at all.[19] Although it seems to be surprising at first glance, there is a plausible explanation for this phenomenon. Unlike typical consumer goods, term life insurance should only be considered if someone has an actual need for coverage. In general, this will entail the existence of dependents that the policyholder wants to protect from financial hardship in the case of his or her death.[20] Hence, the purchase decision is likely to be governed by a two-step process. Initially, consumers evaluate their personal situation and determine whether a mortality risk transfer would be advisable. This phase might be influenced by additional factors, such as risk aversion or a bequest motive. Thereafter, they determine the WTP and select from the range of products that is available in the market.

3.5 Product Switching and Market Expansion Effects

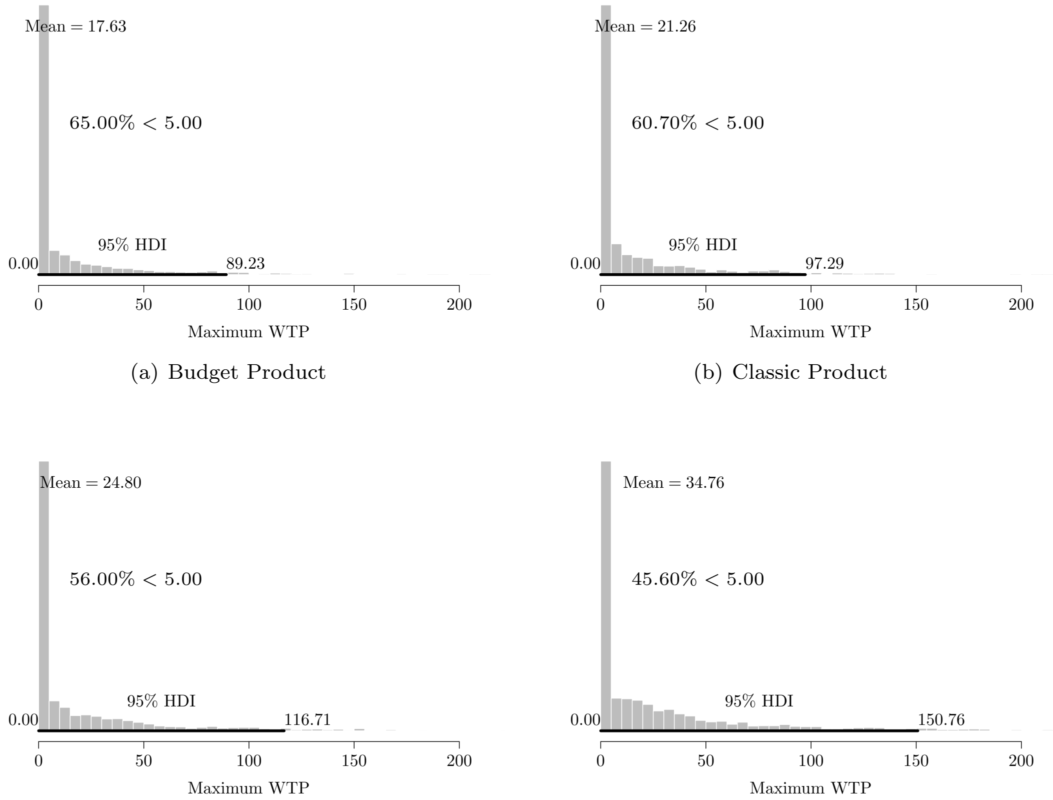
Product Design

In this section, we allow for competition between the four reference products introduced above. Each type of term life policy is assumed to be offered by a different company.[21] Starting from the base case settings in Table 3, we successively apply attribute level improvements and document the associated impact on the shares of preference as well as the revenues of the insurance companies. Before we begin, however, it is necessary to fix the prices at which the contracts are sold in our hypothetical market. In line with its purpose, the budget product is assigned the premium level "very low". The classic and the innovative product, in contrast, will be offered at the "low" price. Finally, in order to purchase the premium product

[19]Note that for some respondents with extreme preference structures, we even estimated negative WTPs. Since those are no reasonable outcomes from an economic perspective, we assigned the affected individuals a WTP of zero.

[20]The perspective of receiving the lump sum from a potential CI coverage alone is unlikely to be a sufficient motivation.

[21]Since consumer decisions will be simulated by means of the first choice method (see Section 2), the results of this analysis are readily transferable to situations in which multiple companies sell the same policy. In those cases, every competitor would capture an equal fraction of the overall share of preference for the respective product.



(a) Budget Product

(b) Classic Product

(c) Innovative Product

(d) Premium Product

Figure 5: Maximum Willingness to Pay for the Reference Products

This figure contains the distributions of the individual-level maximum WTP for the budget, classic, innovative, and premium term life products, including mean and 95 percent HDI. Due to the dominant spike around zero, the fraction of respondents that exhibit a WTP below EUR 5.00 is indicated.

with is highly desirable features, policyholders need to pay the “medium” price. Recall from Table 2 that, depending on the mortality risk group of the consumer, the levels “very low” to “very high” represent different EUR amounts. The results of this simulation analysis can be found in Table 4.

Panel A documents the number of buyers, shares of preference (in percent), and company revenues (in EUR) for the base case scenario. The latter have been calculated by means of a breakdown of the buyers into the ten price groups shown in Table 2. Consistent with our findings for the maximum WTP in the previous section, the last column indicates that 1,155 or 57.89 percent of the respondents choose not to buy term life insurance at all. Among those 840 consumers who actually enter the market, 317 are attracted by the budget and 258 by the premium product. Consequently, the corresponding insurance companies capture the largest shares of preference (15.89 and 12.93 percent) as well as the highest revenues (EUR 6,084.94 and EUR 8,484.41).[22] While being somewhat less popular than the aforementioned alternatives, the innovative product still exhibits almost twice as many buyers as the classic product (175 vs. 90). The direct consequences are a higher share of preference (8.77 vs. 4.51 percent) as well as a larger revenue volume (EUR 4,637.85 vs. EUR 2,097.26).

Furthermore, in Panel B, we report by how many percentage points the shares of preference change, when the attribute level changes indicated in brackets are implemented. Examining the last column, we notice that, owing to the improved designs, some of the individuals that previously decided not to buy now favor one of the four policy types. Hence, all of the considered product improvements help to expand the overall market size, although mostly by a rather small degree. The highest gains in share of preference of 12.48 and 6.77 percentage points are associated with the addition of a CI cover to the budget and the classic product.[23] In the first case, most of the new customers switch over from the innovative product, whereas in the second case, the premium product suffers the largest loss of buyers. Apart from that, strengthening the brand value to become a well-known insurance company seems to be a viable strategy for the providers of the budget and the innovative product. In doing so, they may increase their shares of preference by 5.86 and 6.12 percentage points, respectively.[24] All other modifications, such as a three-item questionnaire instead of a medical examination for the classic product, have a minor impact. Nevertheless, by combining several of these less effective attribute level changes, an insurance company may still achieve a notable extension in its share of preference. Finally, when turning to Panel C, we observe that the four dominant product design improvements identified above are also very attractive in monetary terms. As an example consider the inclusion of a CI rider in the budget product, which generates additional revenues of EUR 3,303.75, implying a growth rate of more than 50 percent.

Price Competition

Apart from product design, insurers may also decide to compete on price. To analyze the associated changes in the shares of preference, we let the monthly premium for each policy vary between the levels "very low" and "very high", while holding those of the others constant at their base case value. The results of this analysis can be found in Figures 6 and 7. On the left hand sides, we show the shares of preference as shaded areas that stack to 100 percent. The products' base case prices are indicated by vertical dashed lines.[25] In addition, the graphs on the right hand sides provide a more detailed view of the underlying product switching and market expansion effects. Overall, three aspects stand out. First, even the lowest monthly premium is almost always insufficient to raise the combined share of preference above 50 percent. Hence, the negligible WTP of many consumers severely limits the potential to grow the total market through price reductions. Second, we observe different demand sensitivities. By lowering

[22] Despite its fewer buyers, the revenues for the premium product exceed those for the budget product, because the former is sold at a higher price.

[23] Although the CI feature clearly has an impact on the product costs, these findings reveal that insurers could add a substantial markup to the monthly premium without suffering a loss of market share.

[24] Obviously it is impossible to change the brand value of a company over night. However, our results provide clear evidence that it may be worth while for life insurers to cultivate a certain degree of popularity among consumers.

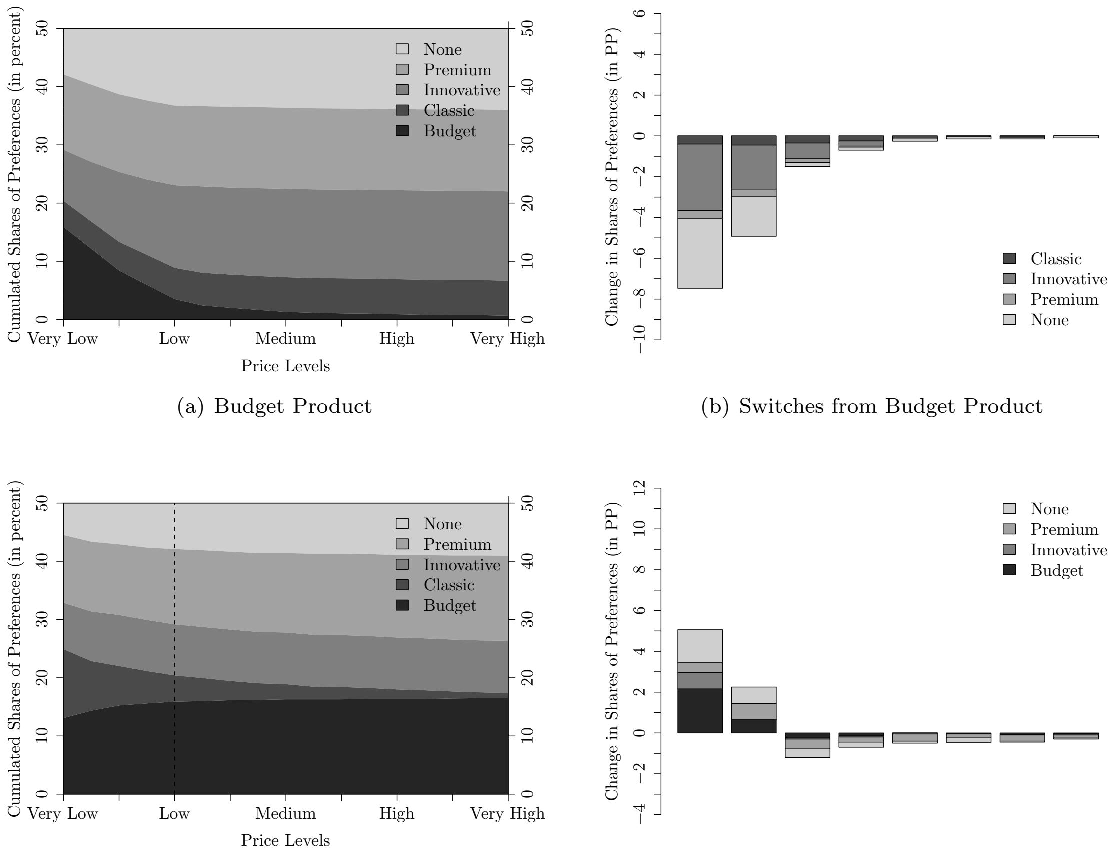
[25] This line is not visible for the budget product because its very low base case price lies at the left end of the graph.

Panel A: Base Case		Budget (B)	Classic (C)	Innovative (I)	Premium (P)	None
Number of Buyers		317	90	175	258	1,155
Share of Preference (in %)		15.89	4.51	8.77	12.93	57.89
Revenues (in EUR)		6,084.94	2,097.26	4,637.85	8,484.41	–
Panel B: Changes in Shares of Preference						
(B)	[10y]	+1.00	0.00	–0.25	–0.10	–0.65
	[3Q]	+1.55	+0.20	–0.80	–0.35	–0.60
	[CI]	+12.48	+0.15	–5.06	–2.61	–4.96
	[Personal]	+0.45	–0.30	+0.35	–0.20	–0.30
	[Well-known]	+5.86	–1.50	–0.90	–1.85	–1.60
(C)	[10y]	+0.05	+0.50	–0.15	+0.05	–0.45
	[1year]	+0.05	+0.95	–0.75	+0.10	–0.35
	[10Q]	–0.15	+0.45	–0.05	–0.20	–0.05
	[3Q]	–0.20	+1.40	–0.15	–1.05	0.00
	[CI]	–0.35	+6.77	–1.15	–4.11	–1.15
(I)	[10y]	–0.40	–0.05	+1.30	–0.10	–0.75
	[3Q]	+0.20	0.00	+0.90	–0.65	–0.45
	[Personal]	+0.20	–0.10	+1.10	–0.75	–0.45
	[Well-known]	–1.45	–0.40	+6.12	–2.56	–1.70
(P)	[10y]	0.00	+0.70	–0.70	+0.55	–0.55
Panel C: Additional Revenues						
(B)	[10y]	+245.75	–	–	–	–
	[3Q]	+464.00	–	–	–	–
	[CI]	+3,303.75	–	–	–	–
	[Personal]	+239.75	–	–	–	–
	[Well-known]	+1,100.50	–	–	–	–
(C)	[10y]	–	+159.25	–	–	–
	[1year]	–	+273.25	–	–	–
	[10Q]	–	+58.75	–	–	–
	[3Q]	–	+343.25	–	–	–
	[CI]	–	+1,350.50	–	–	–
(I)	[10y]	–	–	+233.25	–	–
	[3Q]	–	–	+106.75	–	–
	[Personal]	–	–	+218.50	–	–
	[Well-known]	–	–	+1,253.25	–	–
(P)	[10y]	–	–	–	+305.25	–

Table 4: The Impact of Product Improvements on Shares of Preference and Revenues

This table summarizes the effects of product modifications on shares of preference and revenues of the budget, classic, innovative, and premium term life products. The base case values are displayed in Panel A. Panels B and C contain the changes in the shares of preference (in percentage points) and the corresponding revenue increases (in EUR).

prices below the base case levels, the providers of the innovative and premium products may attract a substantial fraction of new buyers from their competitors and from outside the market. Eventually, the premium product even largely crowds out the remaining policies. A low price strategy for the classic product, in contrast, is comparatively less successful. In all three cases, demand reacts asymmetrically: price increases are associated with much smaller share of preference losses.[26] Third, only the premium policy sustains a noteworthy share of preference in every scenario, no matter whether its own price is increased beyond the medium level or whether either one of the other products is offered at a very low price. Consequently, insurers that understand consumer preferences and design sought-after term life policies may effectively evade price pressure from their competitors.



(a) Budget Product

(b) Switches from Budget Product

(c) Classic Product

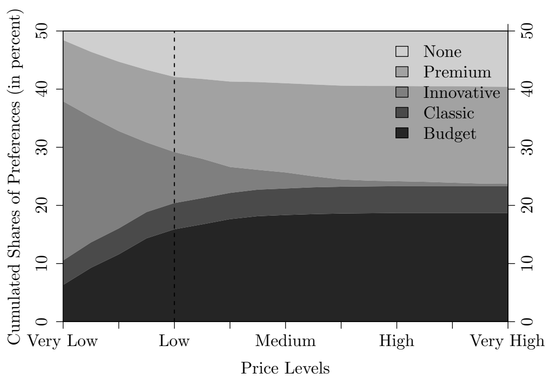
(d) Switches to/from Classic Product

Figure 6: The Impact of Price Variations on Shares of Preference I

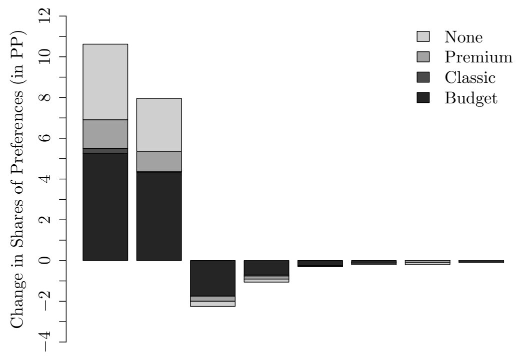
Subfigures (a) and (b) show the shares of preference for different price levels of the budget and the classic product, respectively. The base case prices are indicated by a vertical dashed line and the y-axes have been capped at 50 percent. The associated product switching and market expansion effects can be assessed by means of subfigures (b) and (d). In each case, the prices of the remaining three products are held constant at their base case level.

[26] As the budget product already exhibits a very low price in the base case, we can only make it more expensive, which, in turn, causes a considerable fraction of customers to switch to the innovative product or leave the market.

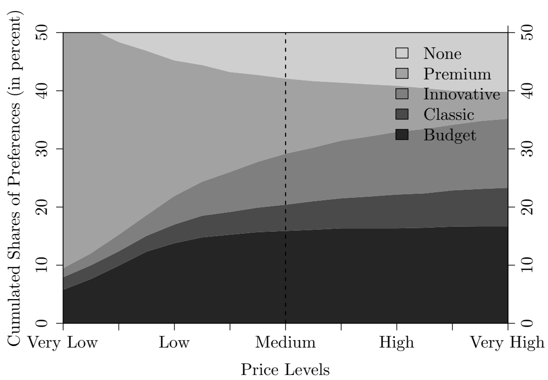
We conclude this section by translating the combinations of monthly premiums and shares of preference from Figures 6 and 7 into company revenues. This is achieved by multiplying the number of buyers in each mortality risk category with the corresponding EUR amounts for the prevailing price level (see Table 2). In doing so, we are able to derive price-revenue curves for the four products, which are depicted in Figure 8. Consistent with the findings discussed above, the classic policy exhibits the least revenue potential, followed by the budget and innovative products. All three curves exhibit their peak at the left end and then fall until they flatten out in a comparable range beyond the middle of the graph. The premium product, in contrast, generates the highest revenues for each price. Even at the level "medium", they still match those that are maximally achievable with the innovative product.



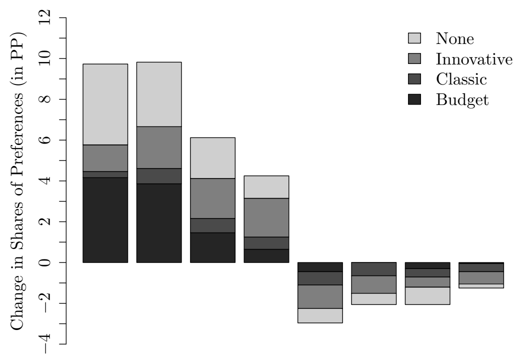
(a) Innovative Product



(b) Switches to/from Innovative Product



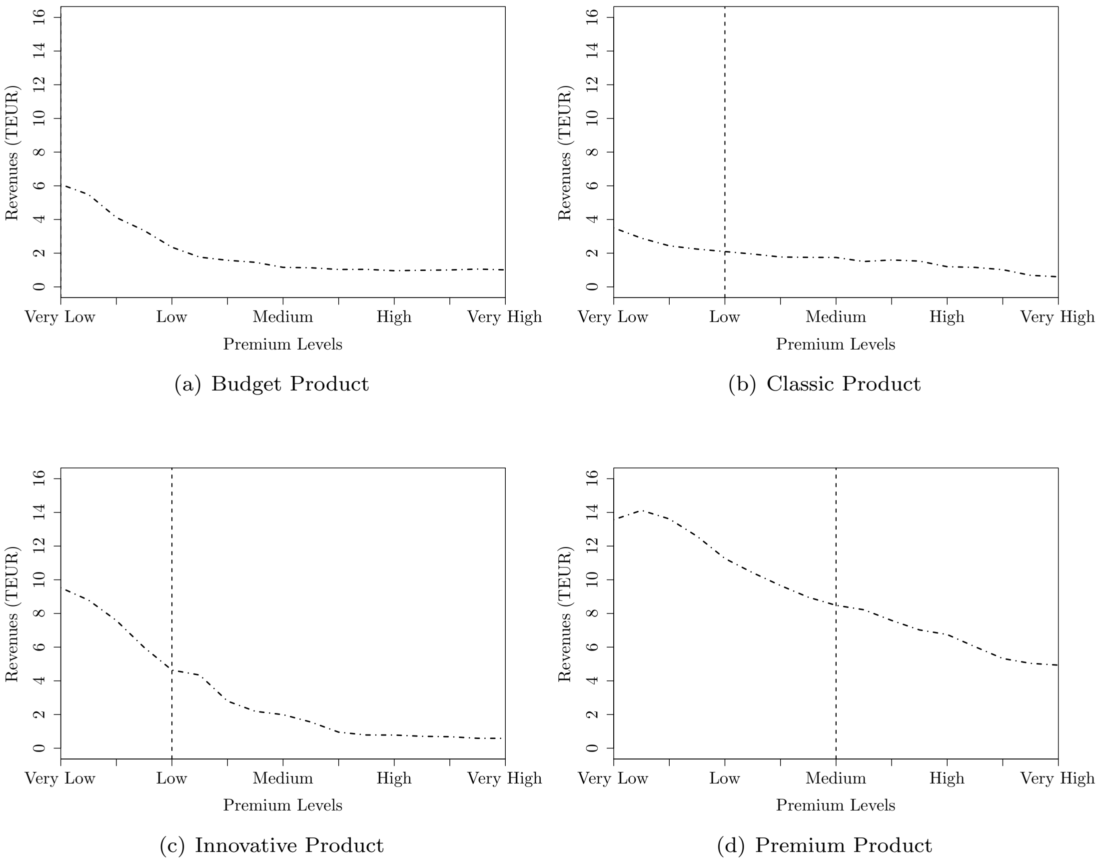
(c) Premium Product



(d) Switches to/from Premium Product

Figure 7: The Impact of Price Variations on Shares of Preference II

Subfigures (a) and (b) show the shares of preference for different price levels of the innovative and the premium product, respectively. The base case prices are indicated by a vertical dashed line and the y-axes have been capped at 50 percent. The associated product switching and market expansion effects can be assessed by means of subfigures (b) and (d). In each case, the prices of the remaining three products are held constant at their base case level.



(a) Budget Product (b) Classic Product

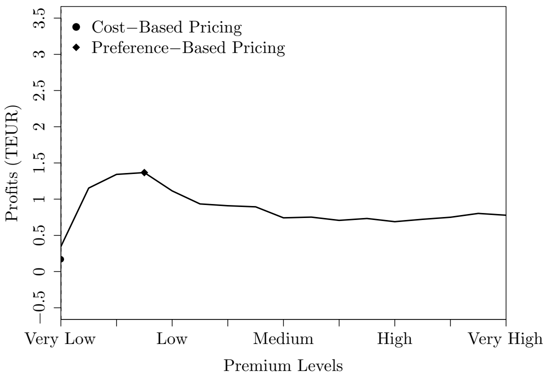
(c) Innovative Product (d) Premium Product

Figure 8: The Impact of Price Variations on Revenues

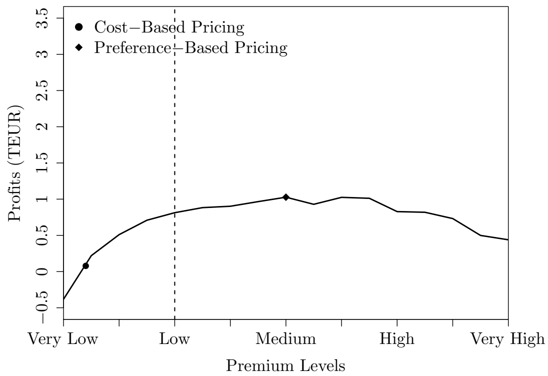
This figure shows the price-revenue curves for the budget, classic, innovative, and premium term life products. The base case prices are indicated by a vertical dashed line. In each case, the prices of the remaining three products are held constant at their base case level.

3.6 Price-Profit Curves

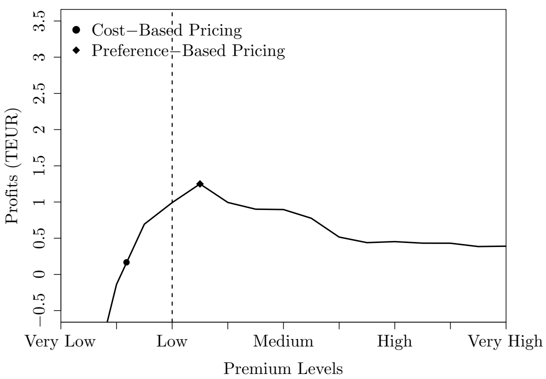
Despite the importance of sales figures and revenues, the shareholders of an insurance company will ultimately be interested in profits. Yet, owing to different variable costs and margins, the revenue-maximizing price does generally not correspond to the profit-maximizing price. Hence, in a final step, we estimate the variable costs of each product for all ten mortality risk groups, derive price-profit curves, and illustrate the superiority of preference-based pricing compared to cost-based pricing. For this purpose, we return to the quotes from the online platform www.check24.de that we employed to set the premium levels in our choice experiments and average those for the youngest and oldest respondent in each mortality risk group. From the resulting figures, we strip a profit loading of 3 percent to arrive at the variable costs of the classic product. In line with its design, the budget product is assumed to be offered by a company with a more favorable cost structure and thus receives a reduction of 15 percent. For the innovative and the premium product, in contrast, we apply a 30 percent markup to the costs of the classic product in order to account for the presence of the CI rider. Finally, the variable costs for the premium product are increased by another 30 percent in order to deliberately handicap the respective insurance company relative to its competitors. All of the aforementioned cost assumptions have been determined based on focus group discussions with market experts from Swiss Re. Table 5 shows the variable costs for each product and mortality risk group.



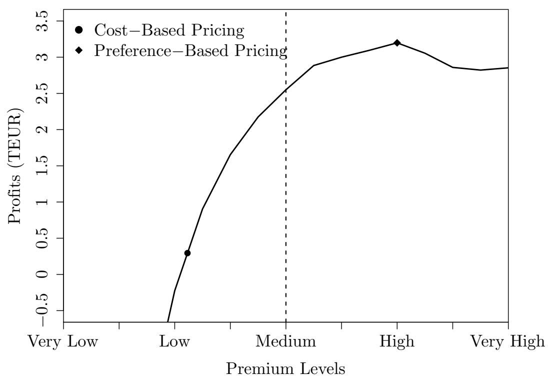
(a) Budget Product



(b) Classic Product



(c) Innovative Product



(d) Premium Product

Figure 9: The Impact of Price Variations on Profits

This figure shows the price-profit curves for the budget, classic, innovative, and premium term life products. The base case prices are indicated by a vertical dashed line. In each case, the prices of the remaining three products are held constant at their base case level. The profits associated with a cost-based pricing approach are highlighted by black dots. The black diamonds mark the maximum profits, which are revealed through preference-based pricing.

The price-profit curves can be found Figure 9. They have been derived by multiplying the number of buyers in each mortality risk group with the respective variable costs and subtracting the result from the revenues shown in Figure 8. At a first glance, we notice that the premium product offers by far the greatest profit potential, which can be accessed through the higher price levels. Consistent with the revenues, in contrast, the price-profit curves of the budget, classic, and innovative products converge to a similar level. Thus, despite the significant cost disadvantage that we imposed on it, the preference-optimized premium product once more proves its superiority in competition. Furthermore, it is now straightforward to estimate profit-maximizing prices. We have highlighted the maximum of each curve by means of a black diamond. Evidently, for all four providers it would be advisable to raise the monthly premiums above their base case levels. The reason is that the increased margins at the new price overcompensate the reduction in the number of purchased policies. Instead of such state-of-the-art preference-based pricing, however, most insurers still rely on cost-based approaches. In order to emulate this behavior, we simply add a fixed loading of 3 percent to the variable costs in Table 5, calculate the corresponding profits, and indicate them by black dots in Figure 9. It becomes clear that, for all four reference products, this traditional insurance pricing method leads to considerable deviations from the profit-maximizing price.

Health	Age Bracket	∅ Budget	∅ Classic	∅ Innovative	∅ Premium
NS	20-29	2.54	2.99	3.89	5.05
	30-39	4.02	4.73	6.15	7.99
	40-44	6.77	7.96	10.35	13.45
	45-49	10.56	12.43	16.16	21.00
	50-54	17.74	20.87	27.14	35.28

Health	Age Bracket	∅ Budget	∅ Classic	∅ Innovative	∅ Premium
S	20-29	4.42	5.20	6.76	8.79
	30-39	9.48	11.15	14.50	18.84
	40-44	18.69	21.99	28.59	37.16
	45-49	31.36	36.89	47.96	62.35
	50-54	54.42	64.02	83.23	108.20

Table 5: Average Variable Costs (in EUR) for the Ten Mortality Risk Groups

This table shows the assumed cost structures for the budget, classic, innovative, and premium product in each mortality risk group. They have been derived by removing a profit loading of 3 percent from the average of the market quotes for the youngest and oldest individual in each group and subsequently applying a 30 percent markup for the CI rider, a 15 percent discount for the budget product and a further 30 percent markup for the premium product.

4 Summary and Conclusion

We run a choice-based conjoint analysis for term life insurance on a sample of 2,017 German consumers using data from web-based experiments. Individual-level part-worth utility profiles are estimated by means of a hierarchical Bayes model. Drawing on the elicited preference structures, we compute relative attribute importances and willingness to pay measures. Moreover, we present comprehensive simulation results for a realistic competitive setting that allow us to assess product switching as well as market expansion effects. Our study provides several important insights. Firstly, although the monthly premium clearly dominates this type of insurance product, brand, CI rider, as well as underwriting procedure were found to be key nonprice characteristics for the average consumer. Consequently, by strengthening the company's reputation, adding a cover against severe diseases, and collecting the customers' medical information via short questionnaires, insurers may substantially boost the aggregate WTP. Secondly, we document a considerable preference heterogeneity. While some individuals are prepared to pay relatively high monthly premiums, a large fraction exhibits no WTP for term life insurance at all, presumably due to the absence of a need for mortality risk coverage. This implies that the total market size can hardly be further increased through product improvements or price reductions. Thirdly, throughout our analysis, the utility-optimized product consistently dominated all alternative offerings. Hence, insurers with reliable preference information will be able to gain market shares, avoid competitive price pressure, and access additional profit potential. Fourthly and lastly, the traditional pricing approaches, which still prevail in the insurance industry, are shown to be clearly inferior to the preference-based methodology that we employ throughout this paper. Therefore, those companies which continue to avoid a real paradigm shift are likely to forgo substantial economic rents.

Despite these contributions, several open questions remain. The fact that consumer preferences for term life insurance were found to be fairly heterogeneous indicates that it might make sense to partition the market. In this regard, one could run a cluster analysis directly on our individual-level part-worth utility profiles. Being based on behavioral aspects instead of demographic or socioeconomic variables, this so-called benefit segmentation has several advantages over traditional approaches. Once the most prevalent consumer groups have been identified, a further research project could then be aimed at assessing the potential of product differentiation strategies and developing an optimal term life portfolio. Furthermore, we have exclusively considered product attributes so far. Therefore, it could be insightful to learn more about the individuals' characteristics, both observable and latent, that drive their WTP. This would allow to more easily differentiate potential customers from those people that cannot be drawn into the market. Finally, one might extend our CBC analysis to other countries with a comparable term life insurance market in order to investigate the role of the cultural environment in this purchase decision process.

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