New Product Sales Forecasting: An Approach for the Insurance Business

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Product innovation is vitally important to the economic success of firms. In today’s deregulated European insurance markets, stagnating growth, increasing competition and new market entrants challenge insurance companies to innovate. At the same time, product innovation is a risky business with tremendous reported failure rates. In consumer goods and durable goods markets, quantitative sales forecasting models based on consumer response are an essential and widely accepted practice used to minimize failure risks. However, although the insurance business has grown into a significant economic sector, reliable scientific studies regarding successful implementations of new product sales forecasting models do not exist so far. Against this background, this paper develops and empirically validates a framework for a quantitative sales forecasting model. The presented approach is based on the principles of simulated test market models. However, as we show, fitting the specific issues of the insurance sector requires major modifications to existing standard models. A real-world application provides promising results and illustrates the value of the new approach.

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1. Introduction

Product innovation is identified as a strategic measure and a creative force which is crucial to the economic success and survival of insurance firms (Hart 1996; Johne & Snelson 1988; Utterback 1994). However, innovations are both vital and risky. New product (NP) failure rates are substantial and failure costs are high. Sales forecasting models are introduced to safeguard against these risks. For fast moving consumer goods (FMCG), simulated test market (STM) models are an accepted practice to estimate the sales potential of NPs before launch. Usually, STM models are low-cost and rapid tools which, besides forecasting market shares or sales volumes, can be used to test pricing, advertising, distribution and promotional plans and to supply actionable managerial diagnostics for product improvement (Heise 2009; Shocker & Hall 1986; Urban & Hauser 1993; Urban & Katz 1983). To forecast sales potential, three types of information fuel the models: product category data, marketing plans and research-based estimates of consumer response (Clancy, Krieg & Wolf 2006). In the nineties, STM models were said to be “the most useful – and certainly most validated – tools in all of marketing research” (Clancy, Shulman & Wolf 1994, p. III).

However, STM models are clearly geared toward FMCG. As outlined below, significant adaptations are necessary if the STM approach is transferred to the insurance business. There are several reasons why sales prediction for the intangible and complex insurance product is a very difficult task (Rushton & Carson 1986; Vermeulen 2004).

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The main challenge results from low consumer interest and expertise, leading to a low propensity to consume (Wehls 2010). Consumers must be convinced of an abstract product that will hopefully satisfy a future need, a concept which is hard to grasp and often implies long-term payment obligations (Köhne & Lange 2009; Menhart et al. 2004; Wilson et al. 2008). Successful STM model applications in the insurance industry, to the best of our knowledge, do not exist so far.

For a long time, NP development generated only minor interest in the insurance industry. In times of regulated markets, NP development was restricted and dampened by its limited scope. In many European countries, however, the current insurance industry is largely deregulated and has changed from a fairly closed sector, with conservative and slowly-operating companies, to an extremely dynamic one (Vermeulen 2004). Although product modifications occur frequently, true innovations are still rare (Kopp 2008). Yet, the latter have become increasingly important in differentiating from competitors (Köhne & Rosenbaum 2004). This implies an increasing need for adequate sales forecasting tools and the ability to deal with the specific conditions in insurance markets. Against this background, an insurance-specific framework for a quantitative NP forecasting model is developed and empirically tested. In cooperation with an international insurance company, surveys for a real insurance product were conducted. The same company also provided required internal data. In this way, the paper aims at filling a gap in NP forecasting research by focusing on the, in this respect, widely unexplored insurance business.

The remainder of this article is structured as follows: In Section 2, we give a brief overview of previous and current STM research and we illustrate its limitation to FMCG and consumer durables. Then, in Section 3, a methodological framework for an insurance-specific NP sales forecasting model is introduced. Model components are discussed along the proposed structure. A first empirical validation in terms of forecast accuracy and robustness (by using data of a real insurance product) is presented in Section 4. Section 5, finally, summarizes required insurance-specific adaptations to existing standard models and discusses directions of future research.

The scope of research is the deregulated European insurance market, with a particular focus on the business-to-consumer sector. Business-to-business solutions are not included in the scope of this paper.

2. Literature Review

STM models are survey-based quantitative structural approaches, using different mathematical-statistical methods to forecast NP sales. STM models became a topic of practical and academic interest during the mid-to-late 1960s when the pioneering works of Fourt and Woodlock (1960) and Parfitt and Collins (1968) appeared. Since then, relevant literature depicts many suggested STM models, including the LTM (Yankelovich, Skelly & White 1981), ESP (Eskin & Malec 1976), ASSESSOR (Silk & Urban 1978) and LITMUS I/II (Blackburn & Clancy 1982/1983). In the eighties, STM models gained popularity in the European market. Research International, for instance, launched SENSOR and MICROTOEST and ACNielsen started to work with QUARTZ. Today, most of these STM models have been redefined or replaced. Still commercially available are BASES (Lin, Pioche & Standen 1982; Shocker & Hall 1986), GFK VOLUMETRIC TESI (Erichson 1997), INNOQUEST*DESIGNOR (Gaul, Baier & Apergis 1996), DISCOVERY (Clancy, Krieg & Wolf 2006) and the fairly new model, LAUNCH EVALUATE, introduced by TNS in 2010. Most of these models are partially published, but due to market research
institutes’ non-disclosure agreements, academic research lacks the models’ complete structure and parameterization. Nevertheless, STM research is still highly relevant. For example, current works address the dynamisation of STM models (Erichson 2008) and the implementation of improved pricing and distribution models, and also report a tendency to micro modelling (Höfer 2010). Furthermore, authors investigate the implementation of multimedia and virtual-reality techniques in STM data collection and discuss linkages of STM modelling to other research areas, such as neuro-market research (Heise 2009; Rumpel 2010). Thus, current research primarily focuses on the optimization of existing STM models for FMCG markets.

Transferring STM models to other industries, such as consumer durables or services, requires the adaptation of standard approaches. The relevant literature provides STM model adaptation examples to durable goods (Lin & Hustaix 1989; Lin, Pioche & Standen 1982; Urban & Hauser 1993; Urban, Hulland & Weinberg 1993). A considerable number of researchers focus particularly on the automotive market (Page & Rosenbaum 1992; Urban, Hauser & Roberts 1990; Urban, Weinberg & Hauser 1996; Urban et al. 1997). In contrast to this, only a few examples refer to STM approaches in the service industry (Hauser & Wisniewski 1982; Lin & Hustaix 1989). To the best of our knowledge, an insurance-specific STM approach has not yet been published.

Because STM models typically make use of different mathematical–statistical methods, providing a sophisticated overview of all approaches would be beyond the scope of this paper. However, existing theories of the preferred methods for the insurance-specific NP sales forecasting model are discussed in the following chapter.

3. Methodological Framework

In this section, a framework for an insurance-specific NP sales forecasting model is developed. Popular STM models provide the basis for this model. STM models usually follow a two-stage procedure. First, researchers consider consumer response to the NP(s) in question, using either a purchase intention survey, a purchase behaviour simulation in a laboratory shop or a preference model (Hammann & Erichson 2000; Schwoerer 1984). As purchase simulations do not match the intangible nature of insurance products, and comparative preference models are less suitable for really new products, a purchase intention measure is chosen for the first phase of the insurance approach. In a second step, consumer responses derived under 100% awareness and availability of the NP are adjusted to correct for the upward bias of an ideal survey environment (Shocker & Hall 1986). Thereby, the model includes all essential steps of the adoption process of a NP (Heise 2009; Stoffels 1989). Referring to BASES (Lin, Pioche & Standen 1986), consumer response is corrected by the target universe, an awareness and distribution stage. In the insurance business, not every consumer is in the market for a new insurance product each year (Clancy, Krieg & Wolf 2006; Lin & Hustaix 1989; Urban, Hauser & Roberts 1990), which requires the definition of a so-called limited target universe. An awareness stage is included, but it needs to fit insurance-specific information channels. Distribution is implemented and fit to the insurance sector by considering shares of personal versus direct sales. Figure 1 summarizes the elements (with corresponding numbers of subsection) that are included in a feasible insurance-specific NP forecasting model. The model components are discussed in addition to the proposed framework structure.

The requirements that an insurance-specific NP forecasting model must fulfil are summarized as follows: The forecast model allows new insurance product sales
predictions for the first three years after launch. It is unrealistic to assume there will be no competitor reaction for a time greater than three years (Menhart et al. 2004). Furthermore, insurance products are often modified after a few years, making precise sales forecasts even more difficult. Forecasts are specified on a yearly basis, although many STM models generate sales forecasts on a monthly or quarterly basis (Gaul, Baier & Apergis 1996; Schomacher 2007). However, the insurance business is less dynamic than FMCG, and the number of new insurance contracts grows much more slowly (Brajak & De Marco 2010; Lin & Hustai 1989). Predicted sales are indicated by the number of insurance policies sold. Besides the expected new contracts per year, the cumulated number of contracts is also provided, taking contract terminations into account. Depending on contract durations, churn rates are derived from the insurance company’s experience with similar products.

Figure 1: Framework of an Insurance-Specific NP Forecasting Approach

3.1 Data Collection

A critical part of the forecast is the measurement of the response of consumers to the NP. Therefore, an insurance-specific concept test must be conducted, following the structure depicted in Figure 2.

Figure 2: Structure of an Insurance-Specific Concept Test

A) In existing STM models, the sample represents a specific group of consumers, which may be all households or a subset, such as buyers in a given product category (Clancy, Krieg & Wolf 2006). Insurance products typically are purchased infrequently and the purchase time is difficult to determine. Therefore, the research requires a limited consumer group that must be defined through a screening section (Clancy, Krieg & Wolf 2006; Urban, Hauser & Roberts 1990). The respondents concerned should show a certain level of interest in the considered product category within the following year.
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Depending on the respective NP idea, this limitation can be complemented with further questions determining relevant target groups for the NP in the first year after launch. B) Another characteristic of the insurance sector is low consumer interest and expertise. Hujber (2005) reveals in her study that 72% of respondents show no or only little interest in insurance products, due to complexity, negative associations with insurance, including accidents and death, and difficulties in evaluating the product quality. Only shortly before taking out an insurance policy, the perceived risk is high enough to ensure a situational involvement in purchase decision (Sutor 2010). Complexity and abstractness evoke uncertainty on the part of potential buyers. Questions about the role of the brand (customer status/relevant set), past buying behaviour and basic attitudes towards the purchase of insurance enable respondents to reflect their future buying behaviour in a more realistic manner. Furthermore, these measurements provide valuable input for the purchase probability predictions (see Subsection 3.4). In order to make interviews easier, reference values should be integrated where possible. Moreover, respondents should be given the opportunity to get back to NP description during the whole concept test phase. C) In the concept-test phase, the NP is introduced in the form of a concept board. This part of the questionnaire comprises the central question about purchase intention as well as further aspects of consumers’ views of the NP. The section is largely based on standard concept tests of STM models, as described by Gaul, Baier and Apergis (1996) and Schomacher (2007), among others. D) The last section covers further determinants of purchase in the insurance sector and thus provides input for adjustment factors (see Subsection 3.4).

In the insurance sector, sales agents and personal selling are pivotal for the NP success (Köhne & Lange 2009). Therefore, the perspective of sales agents should be integrated as well. In particular, insurance products are personally sold via tied agents, independent brokers and bank advisors (Hauser 2009). A survey among all of these groups undoubtedly would exceed reasonable costs. However, insurance companies typically have one dominant personal sales channel which can be used on behalf of all sales groups. In this paper, tied agents are selected because of their dominant role in the German insurance market (Dorka 2010), which is considered for illustration purposes. In addition, tied agents are the major sales channel of the insurance company used in conjunction with this paper for the real world application (see Section 4). Among tied agents, a reduced concept test must be conducted. As in the consumer surveys, the NP idea is introduced by a concept description. However, descriptions tailored for agents are more technically detailed and should contain as much information as possible about planned sales activities, optional discounts etc. The central aspects surveyed among agents are their willingness and intention to recommend and sell the NP. Data of both surveys form the basis for the proposed insurance forecast approach.

3.2 Limited Target Universe

The target universe represents the maximum number of potential product buyers, also referred to as the maximum sales potential. For property and casualty (P&C) insurance, the target universe is defined by the number of households in a country. For personal insurance, the country’s population proves to be an adequate measure. Due to infrequent purchases in the insurance industry, only a small fraction of all potential buyers are in the market each year, leading to a limited target universe per year (Lin & Hustaix 1989). Usually, the marketing management can provide information about the size of this limited target universe. If this is not the case, the necessity of considering a limited target universe can be derived from consumer surveys: A representative sample is invited to the interviews before a limited group of consumers, identified as the relevant target group of
the NP, is selected. Due to the required representativeness of the invited interviewees, the drop-out rate \((DR)\) of appropriate screening questions in percentages can be applied to the target universe (Clancy, Krieg & Wolf 2006). Assuming that the NP under consideration belongs to the dynamic P&C market, the target universe is defined as the total number of households per country \((NH)\). The size of the limited target universe \((LTU)\) is then defined as:

\[
LTU = NH \cdot (1 - DR)
\]  

### 3.3 Modelling Awareness

The awareness stage reflects the share of people who become aware of the NP in the first years after launch. Awareness models are part of most STM models (for an overview see Clancy, Krieg & Wolf 2006; Gaul, Baier & Apergis 1996; Mahajan, Muller & Sharma 1984). Today’s models consider many input variables in forecasting awareness, such as advertising, promotion, sampling, couponing and distribution. However, to reflect adequately the awareness build-up of an insurance product, the mentioned sources need to be adapted. Five sources are considered in the proposed approach: tied agents, sales activities, internet, advertising and recommendation by family, friends or colleagues (referred to as word of mouth in the following), all being crucial points of contact in the insurance sector (Köhne & Lange 2009; Sutor 2010). The survey conducted for empirical validation of the model (see Section 4) confirmed the importance of these sources. At first, each source’s awareness is modelled separately, then all sources are combined in one awareness figure per year.

1) The awareness \((A_{TA_t})\) generated by tied agents per year \((t)\) is comprised of the number of tied agents \((TA_t)\) working for the insurance company, the average number of customers \((REC)\) the tied agents intend to recommend the NP to in the first year after launch and a so-called tied agent experience index \((TAEI_t)\). While \(TA_t\) has to be provided by the insurance company, \(REC\) is derived from the agent survey. The index \(TAEI_t\) considers the fact that agents might change their attitude and sales intention when gaining experience with the NP. \(TAEI_t\) is measured by percentage and must be determined by insurance company experts who are in close contact with sales representatives. Judgement is based on information gathered in the agent survey. All three components are multiplied and divided by the limited target universe. Thus, \(A_{TA_t}\) is a percentage value, representing the share of limited target universe which will learn of the NP due to tied agents:

\[
A_{TA_t} = \frac{TA_t \cdot REC \cdot TAEI_t}{LTU} \quad \text{for } t = 1, \ldots, 3 \tag{2}
\]

2) Besides personal selling, sales activities play an important role in the insurance business. The awareness \((A_{SA_t})\) generated by sales activities is determined based on the number of offers per year \((OF_t)\) that are sent to the target group of sales activities and a factor \((FA_{SA_t})\) that reflects the percentage of the contacted target group becoming aware of sales activities. Both sources must be specified by insurance company experts through reviewing figures of similar sales activities:

\[
A_{SA_t} = \frac{OF_t \cdot FA_{SA_t}}{LTU} \quad \text{for } t = 1, \ldots, 3 \tag{3}
\]
3) Many current STM models imply sophisticated advertising awareness models (Clancy, Krieg & Wolf 2006; Gaul, Baier & Apergis 1996). However, the models’ parameters usually are not published, which explains why these models are not feasible for the current approach. Following the approaches of Haines (1969), Ray (1973), Pringle, Wilson and Brody (1982) and Assmus (1975), a simpler model is determined (for an overview see Mahajan, Muller & Sharma 1984). Taking gross advertising spending ($A_{AD}$) per year into account, the following equation can be specified to determine awareness generated by advertising ($A_{AD_t}$):

$$A_{AD_t} = (1 - e^{-\gamma A_{AD_t}}) \quad \text{for } t = 1, ..., 3 \quad (4),$$

where $\gamma$ is a parameter that measures the effect gross advertising spending in year $t$ has on the awareness. In the following application of the model, $\gamma$ is estimated based on advertising spending and awareness data monitored for advertising campaigns of the cooperating insurance company from 2004 to 2011. With $R^2 = 0.65$, the determined model produces satisfactory results. To apply the specified model for forecast purposes, the insurance company must provide information about expected media spending for planned campaigns in first years after launch.

4) Word of mouth holds a special status within the awareness model since recommendations can be of either positive or negative nature. Following Reichheld (2003), word of mouth is evaluated on an 11-point scale, ranging from 0 to 10 within the consumer survey. At first, positive and negative recommendation shares are derived from low-2 and top-2 boxes of the word of mouth question. Low-2 boxes comprise scale points zero and one; top-2 boxes consist of scale points nine and ten. Positive ($W_{OM_{pos}}$) and negative ($W_{OM_{neg}}$) shares are determined by calculating a weighted average over the two scale points. Then, a net count is computed: $W_{OM_{net}} = W_{OM_{pos}} - W_{OM_{neg}}$. Based on the analysis of insurance net promoter scores (Reichheld 2003), $W_{OM_{pos}}$ and $W_{OM_{neg}}$ are determined in such a way that an average recommendation behaviour results in a neutral $W_{OM_{net}} = 0$, a below average recommendation generates $W_{OM_{net}} < 0$ and an above average recommendation results in $W_{OM_{net}} > 0$. The share of consumers who will be influenced by word of mouth are identified based on an attitude question raised in the consumer survey, denoted as $SH_{W_{OM}}$. $W_{OM_{net}}$ and $SH_{W_{OM}}$ are both percentage values. Thus, the word of mouth factor, $F_{W_{OM}} = 100\% + W_{OM_{net}} \cdot SH_{W_{OM}}$, increases awareness when recommendation behaviour is above average, dampens awareness in the case of below-average recommendation and keeps awareness constant when recommendation behaviour with respect to the NP is average when compared to various observed insurance products.

5) Besides the sources discussed so far, consumers make use of the internet to inform themselves about insurance. Online advertising, e.g. banners, is considered in advertising awareness ($A_{AD}$). But people also seek information on comparison websites (like Check24.de or FinanceScout24.de) and on insurance companies’ websites. Although it is difficult to obtain hard data to describe the intensity of internet usage, click rates of similar NP websites may provide initial hints in this respect and can serve as a reasonable input to the model. As data availability on the web rises extremely fast, internet awareness ($A_{I_{IN}}$) is considered in the awareness model as well.

In order to derive an aggregate awareness from the above sources, three sources are combined first: tied agents, sales activities and the internet. All three sources are both
information and distribution channel and thus are closer to purchasing than advertising and word of mouth. According to Clancy, Krieg and Wolf (2006), and assuming that the usage of these sources is independent from each other, the first aggregation step is based on the following equation:

\[
A_{TA_t/SAt/IN_t} = A_{TA_t} + A_{SAt} + A_{IN_t} - \left( A_{TA_t} \cdot A_{SAt} \right) - \left( A_{TA_t} \cdot A_{IN_t} \right) + \left( A_{SAt} \cdot A_{IN_t} \right) \\
\text{for } t = 1, ..., 3 \quad (5).
\]

In the second step, advertising and word of mouth are added, referring to the structures of the awareness models of NEWS (Mahajan, Muller & Sharma 1984) and BASES (Gaul, Baier & Apergis 1996). Thereby, advertising awareness influences the share of consumers not being reached by tied agents, sales activities or the internet. A dampening factor (\( e \)) considers that advertising has less impact on consumers' willingness to take out new policies. This factor is considered in the BASES model as well (Gaul, Baier & Apergis 1996). \( A_{max} \) denotes the maximum level of awareness an insurance product can achieve. Due to factors like lack of interest in the product category, or "nay-saying" (Pringle, Wilson & Brody 1982), \( A_{max} \) frequently remains below the maximum level of 100% awareness. Its specification can be derived from market research data of similar insurance products. The word of mouth factor increases or dampens generated awareness dependent on recommendation behaviour:

\[
A_{Total_t} = \left( A_{TA_t} \cdot SAt/IN_t \right) + e \left( A_{max} - A_{TA_t} \cdot SAt/IN_t \right) \cdot A_{ADt} \cdot F_{WoM} \\
\text{for } t = 1, ..., 3 \quad (6).
\]

The output of the awareness stage is an aggregate awareness figure \( A_{Total_t} \) for the first three years after launch.

### 3.4 Combined and Calibrated Purchase Intention Measure

In order to get survey-based consumer response, a purchase intention measure is favoured when applying the STM idea to the insurance industry. There is well-founded evidence that stated purchase intentions are positively correlated with behaviour (Bemmaor 1995; Juster 1966; Morwitz & Schmittlein 1992; Morwitz, Steckel & Gupta 2007). Furthermore, purchase intention measures are suitable for intangible products and can be obtained easily and inexpensively within a concept test evaluation (Chandon, Morwitz & Reinartz 2005; Kumar, Nagpal & Venkatesan 2002). However, the relationship between stated purchase intentions and real purchase behaviour diminishes with decreasing product knowledge, decreasing involvement, low familiarity with the product and when the willingness to consult others before purchase is high (Jamieson & Bass 1989; Morwitz, Steckel & Gupta 2007). This shows that converting stated purchase intentions into real purchase behaviour is a difficult task in the present context. In order to generate an appropriate purchase intention measure, several steps of adaptation and stabilization are recommended. Consumer and agent surveys provide the data underlying this step:

1) The insurance business is a push-market (Paprottka 2010) and the personal contact with insurance company agents has a strong impact on consumers' purchase decisions. Therefore, the respondents of the consumer survey are split into two groups. One group that is likely to get in touch with a tied agent of the respective insurance company (agent contact group) and another group for which the personal contact is unlikely (non-contact group). Both groups are identified based on information gathered in the consumer survey. Hints about previous information and purchase behaviour for similar products
reveal the respondent’s tendency to get in contact with a tied agent during the purchase process. The relevant set and customer/non-customer status of the interviewee reveals whether a contact with an agent of the respective insurance company is expected.

2) Within the contact group, the share of people must be defined, which is highly influenced by the consultancy of the tied agents. This group’s stated purchase intentions are typically vague as decision making of consumers strongly relies on agents’ opinions. Therefore, this “agent push” group is filtered out and the stated purchase intention is replaced by the sales intention derived from the agent survey. The agent push group \((AP)\) is identified based on the respondents’ attitudes towards the insurance purchase process: the tendency to delegate purchase decisions, the stated importance of agents in buying decision-making and the level of insurance knowledge. The share of agent push consumers within the contact group is denoted as \(SH_{AP}\).

3) Referring to existing STM models, purchase intention measures are stabilized by combining the stated purchase intention with further purchase determining factors. Thereby, a weighted average of all factors considered is calculated (Clancy, Krieg & Wolf 2006). A typical factor for stabilisation is price value (Clancy, Krieg & Wolf 2006; Jamieson & Bass 1989). In a survey conducted to validate the insurance model under investigation (see Section 4), a further factor revealed an important purchase driver in the insurance business, representing the relevance of the NP. Therefore, both aspects, price value and relevance, are considered in the insurance model. Stabilization takes place on the aggregate level by calculating a weighted average for each category \(i\) of the 5-point purchase intention scale. Weights of purchase intention \((W_{pi})\), price value \((W_{pv})\) and relevance \((W_{r})\) are determined, referring to weights used in the STM model, MICROTTEST. Stabilized purchase intention scores \((PI_{STAB})\) are calculated separately for the contact and the non-contact group, as shown in the following equation:

\[
PI_{STAB_i} = W_{pi} \cdot pi_i + W_{pv} \cdot pv_i + W_{r} \cdot r_i \quad \text{for } i = 1, ..., 5 \quad (7),
\]

whereby \(W_{pi} + W_{pv} + W_{r} = 1\). \(pi_i\), \(pv_i\) and \(r_i\) denote the respective variables’ answer categories, all being surveyed on a 5-point scale and indicated by percentage, with \(\sum_{i=1}^{5} pi_i = 1\), \(\sum_{i=1}^{5} pv_i = 1\) and \(\sum_{i=1}^{5} r_i = 1\). \(\sum_{i=1}^{5} PI_{STAB_i} = 1\) applies accordingly.

Due to the insurance industry’s complexity and abstractness, consumers often have difficulty estimating their future buying behaviour realistically. Therefore, in addition to stabilizing purchase intention on the aggregate level, inconsistencies in consumer responses are adjusted on the individual level by taking other aspects, like openness to switch provider, contractual bonding to other providers and customer loyalty, into account. This adjustment primarily concerns the non-contact group. If this group plays a minor role in the sales of the new insurance product (e.g., if the product is only sold via tied agents, which requires personal contact), this adjustment could be neglected.

Among tied agents, stated sales intentions \((si_i)\) are adjusted by the NPs price value \((pv_i)\), relevance \((r_i)\), overall likeability \((l_i)\) and expected sales potential \((sp_i)\). These aspects turned out to be crucial for recommendation when analysing agent survey data. According to the calculation of the stabilized purchase intention score \((PI_{STAB})\) among consumers, a stabilized sales intention score \((SI_{STAB})\) is determined as follows (using corresponding weights \(W_{si}, W_{pv}, W_{r}, W_{l}, \text{ and } W_{sp}\)):

\[
SI_{STAB_i} = W_{si} \cdot si_i + W_{pv} \cdot pv_i + W_{r} \cdot r_i + W_{l} \cdot l_i + W_{sp} \cdot sp_i \quad \text{for } i = 1, ..., 5 \quad (8),
\]
whereby \( W_{SL} + W_{PV} + W_{R} + W_{L} + W_{SP} = 1 \). The answer categories of all variables \( s_{i}, p_{j}, r_{i}, l_{i}, sp_{i} \) are percentage values and sum up to one when aggregated over the 5-point scale, resulting in \( \sum_{i=1}^{5} S_{i} = 1 \).

The outcome of step three is a stabilized purchase intention measure \( (P_{STAB}) \) for the contact and the non-contact groups among consumers and a stabilized sales intention score \( (S_{STAB}) \) for tied agents.

4) Stated purchase intentions tend to overestimate actual purchase behaviour (Clancy, Krieg & Wolf 2006; Jamieson & Bass 1989; Kalwani & Silk 1982; Lin 1984). Researchers like Lynn, Pioche and Standen (1982, 1986) have been experimenting for many years to create weighting schemes for purchase intention scores, referred to as “conversion rates”. Conversion rates adjust each of the 5-points of the purchase intention scale by converting stated intention into actual behaviour. However, knowledge about conversion rates is owned and withheld by commercial marketing research institutes. For this study, insurance-specific conversion rates were determined based on the expertise of a forecast expert of an international market research company, a literature review (e.g. Clancy, Krieg & Wolf 2006) and concept test data collected for model validation. The combination of these sources created insurance specific conversion rates, \( CR_{i} \) with \( CR_{i} \in [0,1] \) for \( i = 1, ..., 5 \).

5) Taking the insurance specific conversion rates into account, combined and calibrated purchase probabilities \( (P_{p}) \) for agent contact group \( (C) \) and non-contact group \( (NC) \) are defined as follows:

\[
P_{p}^{NC} = \sum_{i=1}^{5} CR_{i} \cdot P_{STAB}^{NC} \tag{9}
\]

\[
P_{p}^{C} = \sum_{i=1}^{5} \left( (1 - SH_{AP}) \cdot CR_{i} \cdot P_{STAB}^{C} + SH_{AP} \cdot CR_{i} \cdot S_{STAB} \right) \tag{10}
\]

6) Besides purchase probabilities of contact and non-contact group, a third aspect is modelled separately on the insurance forecast model’s purchase probability stage, namely the purchase probability due to sales activities \( (P_{SA}) \) in year \( t \). Insurance companies often have access to the success rates of former, similar sales activities. Due to the high quality of these data, they provide good reference values for the NP in question. Thus, case history success rates are preferred to purchase probabilities derived from a consumer survey. The purchase probability due to sales activities is determined based on the number of offers \( (OF_{t}) \) which will be sent out according to planned activities (see also Subsection 3.3, \( A_{SA_{t,n}} \)), the expected success rate of each activity \( (SR_{SA}) \) and the number of households that become aware of the planned activities \( (A_{SA_{t,n}}) \). In Subsection 3.3, this measure was represented by a percentage. \( A_{SA_{t,n}} \) in number of households is obtained as follows:

\[
A_{SA_{t,n}} = OF_{t} \cdot F_{ASA} \quad \text{for } t = 1, ..., 3 \tag{11}
\]

The purchase probability due to sales activities \( (P_{SA}) \) is derived as shown in the following equation:

\[
P_{SA}^{P_{t}} = \frac{OF_{t} \cdot SR_{SA}}{A_{SA_{t,n}}} \quad \text{for } t = 1, ..., 3 \tag{12}
\]
with $SR_{SA} \leq F_{ASA}$ and $p^S_{P_t} \in [0,1]$.

The outputs of the six steps outlined above are three purchase probabilities: one for people likely to be contacted by sales activities ($P^S_{P_t}$), one for the contact group ($P^C_{P_t}$) and one for the non-contact group ($P^NC_{P}$). In a following step, these purchase probabilities need to be linked with the limited target universe and the awareness stage, as outlined in Subsections 3.2 and 3.3. This is done in the subsequent section.

### 3.5 Linkage of Model Elements and Output

In Subsection 3.4, purchase probabilities were determined for three separate groups, while only one awareness figure was generated in Subsection 3.3. As the contact group is much more familiar with the insurance provider than the non-contact group, awareness in the contact group is higher. The same applies to the group contacted via sales activities. Thus, awareness and purchase probabilities are aligned by splitting awareness in the same three subgroups: awareness of sales activities ($A_{SA_t}$), contact group ($A_{Ct}$) and non-contact group ($A_{NC_t}$). $A_{SA_t}$ was specified in Subsection 3.3, whereas $A_{Ct}$ and $A_{NC_t}$ will be defined in the following. Before describing this process, some parameterization and formulas need to be introduced. Let $SH_{SA,C}$ be the share of total awareness generated by sales activities and the contact group and let $SH_{NC}$ denote the share of the total awareness of the non-contact group:

$$SH_{NC} = 1 - SH_{SA,C} \quad (13).$$

All equations presented here can be defined either in percentage values or in number of households, assuming that the NP under consideration belongs to the P&C market. As the awareness split in contact and non-contact groups is solved in number of households, the following relationships are introduced in number of households, indicated with an additional $n$ in the index:

$$A_{Total_{tn}} = A_{SA_{tn}} + A_{C_{tn}} + A_{NC_{tn}} \quad (14),$$  
$$A_{C_{tn}} = SH_{SA,C} \cdot A_{Total_{tn}} - A_{SA_{tn}} \quad (15) \text{ and}$$  
$$A_{NC_{tn}} = SH_{NC} \cdot A_{Total_{tn}} \quad (16).$$

The purchase probability stage and awareness stage are linked as indicated in Equations 17 to 19:

$$p^S_{P_{tn}} = p^S_{P_t} \cdot A_{SA_{tn}} \quad (17),$$  
$$p^C_{P_{tn}} = p^C_{P} \cdot A_{C_{tn}} \quad (18) \text{ and}$$  
$$p^{NC}_{P_{tn}} = p^{NC}_{P} \cdot A_{NC_{tn}} \quad (19),$$

where the variables $p^S_{P_t}$, $p^C_{P}$ and $p^{NC}_{P}$ are the purchase probabilities deduced in Subsection 3.4. $A_{SA_{tn}}$, $A_{C_{tn}}$ and $A_{NC_{tn}}$ indicate the awareness in the respective groups in number of households. Purchase probabilities in percentage values of contact ($p^C_{P}$) and non-contact ($p^{NC}_{P}$) groups are derived from consumer survey data and are therefore not
time dependent. However, when converted in number of households, purchase probabilities are multiplied with time-dependent awareness variables \((A_{ct,n} \text{ and } A_{Nct,n})\), thus becoming time-dependent themselves. Based on Equations 17 to 19, an aggregate calibrated ‘purchase probability’ displayed in number of households is defined as:

\[
p_{ct,n}^{Total} = p_{c_{t,n}}^{SA} + p_{c_{t,n}}^{C} + p_{p_{t,n}}^{NC} \quad (20).
\]

The contact and sales activity groups are expected to take out insurance policies via personal contact, therefore the share of personal sales \((SL_{SA,C})\) is defined as:

\[
SL_{SA,C} = \frac{(p_{c_{t,n}}^{SA} + p_{c_{t,n}}^{C})}{p_{c_{t,n}}^{Total}} \quad \text{for } t = 1, \ldots, 3 \quad (21).
\]

The non-contact group typically purchases via direct channels, notably the internet, thus the share of direct sales \((SL_{NC})\) is specified by \(p_{p_{t,n}}^{NC}/p_{c_{t,n}}^{Total}\). Starting from this specification, \(SH_{SA,C}\) and \(SH_{NC}\) are determined based on the NPs planned distribution. Based on past experience with similar products, the insurance company fixes the expected share of personal \((SL_{SA,C})\) versus direct sales \((SL_{NC})\). Due to the functional linkage between the awareness and the purchase probability stage (cf. Equations 17 to 19), the awareness share \(SH_{SA,C}\) can be determined by solving a simple optimization algorithm. This means that \(SH_{SA,C}\) is specified in a way that Equation 21 applies. Then \(SH_{NC}\) is derived from Equation 13 and \(A_{ct,n}\) and \(A_{Nct,n}\) are calculated using Equations 15 and 16. Awareness in percentage values for contact and non-contact groups are defined as shown in Equations 22 and 23:

\[
A_{ct} = \frac{A_{ct,n}}{A_{Total,t,n}} \quad \text{for } t = 1, \ldots, 3 \quad (22) \text{ and }
\]

\[
A_{Nct} = \frac{A_{Nct,n}}{A_{Total,t,n}} \quad \text{for } t = 1, \ldots, 3 \quad (23).
\]

Finally, sales forecasts \((SF_t)\) for the first three years after launch are obtained by making use of the following equation:

\[
SF_t = LTU \cdot A_{Total,t} \cdot p_{p_{t}}^{Total} \quad \text{for } t = 1, \ldots, 3 \quad (24).
\]

Variable \(LTU\) was specified in Equation 1, \(A_{Total,t}\) in Equation 6 and \(p_{p_{t}}^{Total}\) is defined as a percentage value, with \(p_{p_{t}}^{Total} \in [0,1]\):

\[
p_{p_{t}}^{Total} = A_{SA,t} \cdot p_{p_{t}}^{SA} + A_{ct} \cdot p_{p_{t}}^{C} + A_{Nct,t} \cdot p_{p_{t}}^{NC} \quad \text{for } t = 1, \ldots, 3 \quad (25).
\]

### 4 Empirical Validation and Findings

In order to test the proposed insurance forecast model’s practical suitability, it is applied to a leading international insurance company’s existing product. For model validation, the availability of real sales data for the first three years after launch is crucial. Therefore, a previously launched test product is selected. Survey data revealed 23.3% product awareness, meaning 76.7% of respondents received a NP situation. In favour of sufficient data availability for model validation, this minor bias was accepted. The product
belongs to the more dynamic P&C business and is assigned to the house and home category. Online concept test surveys were carried out among consumers and tied agents of the cooperating insurance company. Weights and parameters were aligned with insurance company experts and an international market research company’s forecast expert.

Expected new contracts and cumulated contracts for the first three years after launch were calculated, according to the explanations presented in the preceding section. Forecasted and observed sales are then compared, which provides the percentage deviations per year, as shown in Table 1. In all three years, the forecasted new contracts slightly underestimate real sales ranging from a -1.2% deviation in year one to a -6.9% underestimation in year three. The forecasted values are considered to fit well with the real sales, particularly when taking into account that prestigious market research institutes promote an average STM model forecasting accuracy of +/-9% deviation from real sales (see ACNielsen 2013; Ipsos 2013). In all three years, the obtained percentages remain below this reference value. On a cumulated level, the forecasts are even more precise. In all three years, absolute deviations remain below 3%.

Table 1: Percentage Deviations of Forecasted and Observed Sales of the NP

<table>
<thead>
<tr>
<th>Percentage deviations of forecasted and observed sales of…</th>
<th>new contracts per year</th>
<th>cumulated contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Y1</td>
<td>Y2</td>
</tr>
<tr>
<td></td>
<td>-1.2%</td>
<td>-3.8%</td>
</tr>
</tbody>
</table>

In order to test the model’s robustness, different extreme but realistic scenarios were investigated (see Table 2). Plausibility checks with the cooperating insurance company’s data and experience, like information about shares of sales provided by agents, awareness levels of advertising campaigns and the sales impact of sales activities, are feasible for scenarios two through four in the below figure. These scenarios simulate the expected decline in sales if no agents, no advertising or no sales activities accompany the launch of the NP. Thereby, the strength of drop strongly depends on the intensity of agent-push, advertising campaigns and sales activities of the respective test product. In all three cases, the model delivers very plausible results. Scenarios five to seven were used to test forecast accuracy of simpler model variants by skipping different steps of the adjustment and stabilization process. As was expected, forecast accuracy declined in all three cases. Splitting consumers into contact and non-contact groups turns out to be particularly important to obtain forecast accuracy. In the present case, consumers and tied agents share a similar view of the product, thus the omission of sales intention of agents (Scenario 7) has only minor effects on the overall predictive accuracy. Anyhow, the opinions of consumers and agents might diverge more for other products; hence, the implementation of sales intentions is recommended for further applications. The presented scenarios confirm that the proposed approach complies with requirements of practically applicable marketing models proposed by Little (2004): robustness and completeness.
Besides its above illustrated usefulness for sales forecasting, the model can be used to simulate the impact of advertising efforts, sales activities and planned distribution. Furthermore, model applications supply actionable managerial diagnostics for product improvement like awareness, purchase probabilities and attitudes of different consumer (sub)groups, their likes and dislikes, as well as detailed information about the sales agents’ perception of the new product. Thus, the proposed quantitative new product sales forecasting model provides a sophisticated tool for the insurance business which delivers managers a structured guideline to successfully estimate market opportunities of innovative insurance products. The cooperating leading international insurance company already decided to apply a computer-based version of the suggested approach for further product innovations.

5 Summary and Conclusions

In this paper, an insurance-specific forecasting model is developed and empirically tested, which estimates the expected cumulated sales of an innovative product for the first three years after launch. Thereby, the influence of advertising campaigns, sales activities and planned distribution on sales is considered. Focusing on characteristics of the widely under-researched insurance industry requires extensive adjustments of existing models serving similar purposes. Notable adaptations are the inclusion of product-specific screening questions which allow for the definition of a limited target universe and the implementation of an insurance-specific awareness model. The importance of personal sales roles is considered by splitting consumers into an agent contact and non-contact groups. Furthermore, the perspective of sales agents is evaluated in a separate survey and the stated purchase intention of people with high affinity to consultancy is replaced by the sales intention of agents. Behavioural uncertainty and below-average expertise of consumers are handled by adaptations of the questionnaire as well as on an analytical level.

The application of the new approach to a real insurance product provided promising results regarding the sales forecasts’ accuracy and plausibility. Nevertheless, further empirical investigations are necessary to support the results presented here. Future investigations should include additional applications in the discussed P&C business but
might also be expanded to other lines of business, like life and health insurance as well as the corporate client business. However, the long-term character of life insurance and the higher perceived risk pose further challenges to consumer response handling while the corporate client business is characterized by professional purchase behaviour (Vielreicher 1995). Due to the lack of appropriate advertising data, a simplified advertising model is incorporated in the outlined model. However, more sophisticated approaches have already been proposed (Clancy, Krieg & Wolf 2006; Gaul, Baier & Apergis 1996). Though the simplified approach’s predictive accuracy is satisfying, the calibration of a more sophisticated advertising model would be desirable. Further research in the insurance-specific conversion rate arena would be favourable as well in order to guarantee reliability and robustness of the figures obtained.

References


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Kaltenbacher & Decker


