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Multi-Policy Synergies: A Data-Driven Analysis of Consumer Behavior and Cross-Selling Strategies in Auto, Home, Life, And Umbrella Insurance

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Abstract

In the market of insurance products, brand-specified policies are often sold under a "multi-policy discount" by the same firm. Such multipolicy discounts are viewed as a means to encourage policyholders to cross-buy or bundle several policies offered by the same firm. The bundling type of cross-selling strategy associated with multi-policy discounts is becoming increasingly prevalent in the property-casualty insurance industry.
Nevertheless, as the insurance market and the cross-selling strategies become more complex, the effectiveness and efficiency of these bundling type of cross-selling strategies and the mechanism through which they work are less understood. The consumer purchases multiple policies from the same firm can be dependent not only on the discount offered on the multi-policy but also on the preference for the discounts on individual policies, the multi-policy and the individual policies offered by other firms with similar product. Such a phenomenon is labeled as “chaining preference” in consumer choice theory, but it is seldom examined in existing econometrics for the insurance market invoking the true and latent utility frameworks.
It is worth noting that the effectiveness and efficiency of discount policies depend on a proper consideration of not only the true utility parameters but also the latent utility. An extensive literature has emphasized the importance of accounting for the unobservable effects in modeling and analyzing consumers' behaviors. On the other hand, the latent utility framework modeling the joint distribution of true and latent utility has attracted recent attention, but most of existing applications have focused on single purchase scenarios. This paper, thus, aims to evaluate the effectiveness and efficiency of the multi-policy discount policies taking into account this chaining preference by using the newly developed latent utility framework. It will be of great significance to the newly emerging question of bundling or multi-product discount policy in marketing and pricing research.

Key words : Multi-policy synergies, cross-selling strategies, consumer behavior, auto insurance, home insurance, life insurance, umbrella insurance, data-driven analysis, customer segmentation, policy bundling, customer retention, purchase patterns, insurance marketing, behavioral analytics, product diversification, upselling, insurance portfolio, customer lifetime value, risk assessment, personalized offers, multivariate analysis, predictive modeling, insurance cross-sell optimization, policyholder engagement, coverage overlap, customer acquisition, insurance preferences, multi-line discount strategies.

1. Introduction

Consumers typically buy multiple products from the same insurance firm (the insurer) because product lines are complementary in nature; this is usually known as a “multi-policy” offered by the insurer. Multi-policy holding generates a potential revenue source for insurance firms; for example, multi-policies could simply enhance the revenue from the current customers. As a result, increasing multi-policy holds has been one of the targets for many insurance firms in the world. However, research of consumer behavior in response to multi-policies is lacking although it is an important aspect for the insurance firms to have a better overall marketing strategy such as bundling and cross-selling products. In view of this importance, Light is shed on both theoretical and empirical understanding of consumer behavior in the presence of multiple policies regarding consumer’s conversion, bundling preferences and cross-selling [1]. Empirical evidence shows that insurers can facilitate consumers to move under their management in a natural way. A firm candidate can convince those individuals who have not yet adopted any policy under its management, or those who currently own a policy issued by another firm, to adopt a policy and/or terminate its current policy under another firm. Firms are allowed to cross-sell additional policies to current consumers who already own at least one policy. It is found that consumers’ conversion behavior varies across policies with different characteristics, composite analyses reveal that policyholder’s cross-policy and cross-firm responses to multi-polices are also characterized by comparative rigor.

2. Literature Review

This section reviews the existing literature on the topic of insurance consumer behavior with respect to multi-policy or cross-selling. It highlights key findings related to customer acquisition cost, the market structure of the Bermuda insurance market, short- and long-term panics in insurance markets, and exercise behavior in universal life insurance.

Most existing studies focus on another collective term of policyholder behavior: customer acquisition cost models. This literature estimates the customer acquisition cost of insurance companies with respect to the profit and loss canopy model. It studies either auto or home insurance data with respect to exogenous shocks on a particular day. It shows that auto policyholders only respond to shocks on their own industry but there is a portfolio effect on P&C policyholders buying from other industries. With respect to Bermuda market structure, this study records the introduction of dependent capital in the Bermuda insurance market and develops a model that reflects the roles of both new and old capital on the price of coverage and the market structure as a mixed oligopoly. One key finding is that a restricted number of old capital firms provide profit neutrality to new capital firms.
Another important stream of research aspect is the short- and long-term panics in insurance markets. This literature assesses the short-term and long-term abruptity of casualty events in property & casualty insurance markets. It exploits significant events and finds a premium increase as well as a drop in policy count. It properly argues against the rational consequences of such abrupt events and identifies supply limitation as a plausible driver of long-term panics. In the short- and long-term mindset of agents, the current literature studies the optimal stochastic retirement age for agents with both uninsurable investment return risk and mortality risk. The usage of analytical approximations to widely observed representations of mortality rates is highlighted and estimated. The only identified individual-optimal variables are rates of consumption or expenditure. Key features of exercise behavior in universal life insurance are determined empirically. In particular, demand curves for lapses are found to vary significantly as a function of the amount surrendered.

3. Methodology

To the best of our knowledge, insurance research has not yet formally studied the impact of a newly acquired insurance policy on another one in terms of its features. Insurance policies are characterized by their insurance coverage, policy types, and policy features. However, most empirical research considers just one of these three aspects in isolation. The potential synergies in these dimensions among different policies are ignored. The main challenges include the difficulty of acquiring a sufficiently large data set that has diverse policies and the development of an appropriate empirical modeling framework.
First, the researchers develop an approach that combines a dynamic class of insurers and consumers with a rich data set of those insurers and their individualized offers and policies. A unique aspect of the data is that it includes some policyholder characteristics, auto insurance characteristics, and individuals' enrollment in those insurers across time, but few details on the insurance offer history. To avoid losing information, the researchers propose to partially disaggregate the insurers and integrate those hidden variables.

Fig 1 : Define Steps of Research Process in Research Methodology

Second, they establish how the newly obtained policy affects the other one among a class of consumers. The treatment is that consumers acquire a new policy, while the control is the case of no new policy. The key to inferring the cross-effects is to recognize that the two policies interact through the consumer's chosen policy features.
Third, they utilize a broad set of consumer characteristics and auto insurance policy characteristics that are easy to obtain and are also relevant for prediction as the basis on which to evaluate the impact of the treatment. Consumers' evaluations of the purchase are proxied by their chosen policy features and hence calculated by the associated cross-indices. Their result that the new auto policy increases the payout and reduces the risk coverage of the existing home policy suggests that securing home damage at a lower cost becomes a priority with the amount of excessive risk coverage. It shows a different role for the new life insurance policy on existing life insurance plans. Since its premium is diminishing compared with the risk coverage, it is more likely that the new policies are intended to afford home mortgage protection and even loan mortgage protection.

3.1. Data Collection

Once a customer purchases homeowners' insurance, cross-selling is modeled as an impact on the current probability of purchasing automobile insurance and its timing. Data on individuals who purchased homeowners' insurance from a leading insurance company from 2005–2012 is analyzed. The dataset contains policy information over time that allows the tracking of individual customers' purchases of auto or homeowners' insurance. The data also contain a rich set of variables. In the modeling stage, to account for the impact of customers' policy information, a bivariate probit model that allows for correlation to cross-sell homeowners' insurance is estimated. Three different bivariate probit models with customers' policy characteristics, demographics and cumulative purchase amounts are estimated. In the modeling of the timing of cross-selling, time-dependent variables are constructed indicating the time elapsed since the last purchase. A Cox proportional hazards model is used for the analysis. Overall, cross-selling proposals are provided based on the analysis findings on whether or when each customer is likely to acquire homeowners' insurance [3]. To test the cross-selling model, the dataset from the first household insurance company is used. The dataset contains homeowners' insurance policy information for households that purchased insurance for the first time between 1 March 2005 and 31 March 2012. The policy information includes the arrival or lapse date, and a unique identification number for each policy. Households that purchased homeowners' insurance for the first time are only targeted. Households that purchased personal insurance such as automobile, fire, or damage insurance other than homeowners' insurance are excluded. To control for external shocks, historical product launches and other activities by the company are also excluded. Using this dataset, customers whose information covers every month in the modeling period are tracked. It is assumed that customers with no policy at any observation point are not included. After excluding households with missing values, a dataset consisting of 92,077 households is analyzed.

3.2. Analytical Framework

A consumer who is offered insurance coverage in several categories (life, car, home, etc.) can be thought of as a multi-policy consumer. Marketing effectiveness varies across agencies (or segments), and consumer behavior is determined by both consumer (or agency) turnover and differential agency marketing effectiveness. From an agent's perspective, there are two questions: how many consumers can be acquired and where are they located? Another important decision for an agent is whether to market a new or a used vehicle. Within a segment, marketing decisions should reflect past consumer behavior: marketing to non-consumers decreases as the number of vehicles still owned increased. In the context of a competitive market on the retail side and information asymmetry on the wholesale side, several strategies are examined in a differential game over continuous time and develop an observable state-space equilibrium. The decision-making process of a multi-policy consumer requires careful examination. Rather than purchasing various individual insurance plans from multiple insurance companies, it is a common practice for consumers to include all of their coverage needs in what is known as a multi-policy plan. Consumers doing this purchase several insurance products from a single insurance company. A more precise assessment of the potential of a cross-selling opportunity is needed to support planning decisions, including the coordination of marketing measures for that opportunity. It is first established that firms offering products in different categories can profitably cross-sell them, even without targeting and even when the products are unrelated. Given network data, it is then shown how to quantitatively model potential cross-selling opportunities. Consumer behavior is modeled with means restricting a multinomial logit choice model by means of a latent Markov chain, which captures how latent product affinities evolve over time. Advances in numerical methods allow us to infer the parameters of such a model from large data sets, including large and complex data sets, using general-purpose statistical software. Using data from a consumer network in the car insurance market in Germany, the model is used to demonstrate the importance of accounting for both consumer behavior and product characteristics o consumer affinitized when crafting cross-selling strategies.

4. Consumer Behavior in Insurance

Many companies offer multiple insurance contracts to their consumers. Consumers are typically believed to be heterogenous both in demand for multi-policy coverage and subsequent exercise behavior. Insurers actively pursue cross-selling strategies by designing attractive multi-policy discounts. Given data on the complete consumer base consisting of multi-policy consumers, single-policy consumers, and consumers who changed coverage, the problem is how to effectively estimate an individual-level dynamic, structural model of demand with multi-policy synergy effects, specifically regarding partly observed past policyholder behavior .

Focusing on a property insurance provider affected by market entry and exit, it analyzes cross-selling strategies with respect to the type of states consumers occupy, specific policy characteristics, and type-related preferences. The estimated dynamic model provides insights into equilibrium policyholder behavior such as (i) multi-policy and cross-selling strategies, (ii) multi-product interaction effects in general, and (iii) the need to focus on existing consumers and test specific cross-selling strategies. Implementation is illustrated by using some stylized scenarios and providing counterfactual predicted choices, together with a simulation-based estimation procedure using a minimum distance estimator. The estimation strategy is based on diversity of past policyholder behavior and a sufficiently large consumer base.

Fig 2: Consumer Behavior: Types, Theories, Models, Tools & Scope

Catering for different consumer types accommodating heterogeneous risk preferences, demographic factors, and hedging motives. The results reveal that ignoring consumer heterogeneity yields a markedly lower likelihood of observed policyholder behavior and enhances the estimated franchise value. The model presented is capable of realistically describing the dynamics of general, and insurer-limited cross-sell policyholder behavior while accurately estimating unavailable policyholder characteristics such as the persistent premium increase. Moreover, multi-policy impacts on observed policyholder behavior and policy value are analyzed in detail.

4.1. Understanding Consumer Preferences

Having observed that consumer multi-policy hold behavior is not universally prevalent, the first study asks "What drives consumer preferences for or against multi-policy hold?" Specifically, the analysis focuses on exploring the systemic and behavioral attributes that drive consumer preference heterogeneity across product types. Weekly shopping data from household portfolio are used to capture product types and reveal multi-policy hold behaviors. Systemic factors are consumers' fixed attributes, representing their market environments and demographic information. Behavioral factors are consumers' updated attributes, capturing their shopping behaviors and risk attitudes in the market. A multi-group latent class analysis was performed to uncover consumer preference classes and intentions toward multi-policy hold. The estimated choice model is then evaluated against an experimental scenario quantifying the willingness-to-transact across product types. The insights from this study can benefit insurers' product development, customized communication strategies, and cross-selling initiatives to increase consumers' multi-policy hold behavior [1].

The general risk factors taken into account are risk characteristics, loss ratios, and portfolio loss ratios. The economic factors directly affecting the premium are loss-related economic conditions such as GDP growth, underwriting performance, and changes of fee income. The security features represent the structural aspects of the insurance company including risk retention, reinsurance structure, product mix, investment structure, and equity benefits. The institutional factors include local regulation variables, share turnover, market concentration, and number of insurers. The conditional loss distribution is specified as a mixture of normal distributions by using as many components k=1 to k=8 and conducting a mixture model selection. Then the β's, the coefficients of risk factors are forecasted for a quarter.

A panel data system including both the direct and the indirect influence factors could therefore be constructed with the independent variables containing the first three elements, and the dependent variable LMDAC. In fact, estimating a HAC panel data regression model requires both a bracketed data matrix and its moment ratio outputs which are large in number in this case of high-dimension. The realizations on IIDS residual sequences are collected to estimate and save these data surfaces with time-consuming bootstrapping. In order to keep sufficient variation in cross section along with strong time series such p=13 is chosen to be 12-dimensional only by keeping 5 economical factors, 6 security factors and 1 institutional factor, thus enhancing the estimation efficiency.

4.2. Factors Influencing Policy Selection

Not surprisingly, consumer preferences are key determinants for policy selection. This comprises three kinds of preferences that concern the policyholder's behavior towards the native insurance product as well as other financial products. First, policyholders might have a preference structure that is a combination of linear and non-linear preferences with regard to wealth. Second, the propensity to understand insurance contracts could be a key characteristic of consumers, which likely determines the extent to which policyholders are aware of policy options and their peculiarities. Consumers may exhibit different degrees of product awareness. Some find new products through advertising and are aware of many alternatives, while others are unaware of available products or options. Product awareness (cognitive cost) can, for example, be operationalized by the number of insurance policies chosen by a consumer and the duration of memberships. Third, consumer complexity averse might tend to stick to single policies. Complexity aversion could arise from a limited ability or unwillingness to process information, rendering consumers more reliant on standard options or 'default' choices

Fig 3: The importance of consumer behavior and preferences

Alternative internal choices models, driven by representations of policyholder decisions as Bayesian updaters of their prior beliefs about the adequacy of policy conditions, could be employed for parametric, non-parametric, or German multifactor controls for cross-selling spillovers. Multi-product pricing schemes might require more coordination among business units and cross-selling advances compared to single-product ones. Consumer policy selections could depend on policyholder networks and recommended products, e.g. in family or snack bar scenarios. These multi-policy preferences can be simulated utilizing graph theoretic approaches in combination with network theory. With sufficient technical depth, simulation designs could be feasibly conducted with existing software for agent-based simulation or Q-Lab. Adverse consumer selection on new policies across departments might dilute risk assessment quality. The effects on solvency requirements and profit margins can be analyzed. The product understanding of consumers might differ across cross-sales. Product knowledge and mistrust can be addressed in formative surveys or by means of dispositional forecasting scenarios.

5. Cross-Selling Strategies

Cross-selling is a firm practice whereby customers acquire multiple products or services from the same firm [5]. This practice occurs across various industries, including retail, banking, insurance, telecommunications, hospitality, and e-commerce. Although cross-selling initiatives are in place, many insurance companies and banks face challenges in increasing their life insurance or saving fund policy base. With the low pre-purchase policy fobs, they have initiated cross-selling campaigns of life policies to their clients with non-life products. The effectiveness of these campaigns seems to be out of consideration by product managers. The risk of unsuccessful cross-selling attempts in revenue cycles and operational hurdles to servicing such policies encourages research into the customer base of non-life products in general insurance firms. A few possible findings could give lenses to consider customers to approach for cross-selling of life insurance policies or saving fund policies.

Cross-selling can also take the form of "up-selling," whereby the firm's goal is not to sell more than one product type but, rather, to induce the customer to migrate toward higher profit versions of required products, upgrades, and add-ons. For example, car insurers commonly provide add-on products to clients according to different budget elasticity observations. Cross-selling is the decision for a firm to offer products of additional categories to a customer after the first transaction product choice, while in the up-selling case, the product manager aims to increase the value of the product already chosen by the customer. Consequently, the term "cross-selling" can be used to cover both product category extension and product variant extension practices. Cross-selling commonly involves the decision of which potential customers in the current customer base to target and which product to offer. Cross-selling refers to a situation in which a customer leaves a purchase transaction to acquire other product services, and this effect is also observed by long-tail products offered by internet firms.

From a managerial perspective, there are many reasons why the implementation of a successful cross-selling policy is an important objective for a firm. First, an obvious point is that customers benefit from having fewer points of contact when looking to buy products. This might result in reduced administrative costs and errors and, overall, a reduction of the time needed to search and acquire products. Formalizing the relationship with an additional product service through the same firm increases reliance on the company and strengthens the link between the user and the provider. In fact, on the one side, it has been found that a value-added service tends to raise the switching costs of the client; on the other side, service transition is known to be smoother for economies of scope providers. Second, firms also benefit from focusing on current customers rather than constantly acquiring new ones. According to research in customer relationship management, firms that target their existing customers rather than untapped prospects can expect to face much lower transaction costs.

$$\text{Cross-Sell Revenue} = N \times C \times A \times R$$

Equation 1: Cross-Selling Revenue Equation

Where:

- N = Number of existing customers targeted
- C = Conversion rate (percentage of customers who purchase additional products)
- A = Average number of additional products purchased per customer
- R = Average revenue per additional product

5.1. Definition and Importance

Insurance multi-policy discounts are of great potential value to applicants and insurers alike. Therefore, discovering which customers are likely to ask for multi-policy discounts is of paramount importance to insurance companies. Modeling whether a consumer is likely to own several policies is an important data mining problem in the insurance business. The outcome of this study can be used to devise cross-selling strategies for consumers of one policy product to be offered with multi-policy discounts. This survey demonstrates how to use data mining methods to plan and analyze cross-selling strategies using consumer data. In addition, a procedure is provided to assess the potential worth of different target customer subgroups [6]. This research estimates the worth of various target customer segments and uses the insights for targeted, smart marketing strategies. This study utilizes Naive Bayes Models to analyze consumer behavior in making multi-policy decisions based on their single insurance product choices.

Analyzing cross-selling strategies using consumer behavior features necessitates the use of a complex model. Many consumers with multi-product insurance are similar to those who only have a single policy since insurance products often have different target groups. Therefore, it is particularly challenging to find a good estimate of the probability that a consumer with a single insurance product has more than one policy considering that it is a rare event [2]. In addition, the number of jointly owned policies the model needs to predict is larger than two. For instance, it is assumed that one insurance product is owned considering that consumers often have multiple policies. Where consumers have different first policies, cross-sell offers must also differentiate second products. As a result, a different choice of a second policy is most often used for the second product. These two characteristics of the problem lead to a very ill-knot model case where near total absence of observation and increased complexity of modeling the multi-product states does not balance prior knowledge of the product. Hence, a relatively simple model of naive Bayes was chosen to model consumer choice of policy product.

5.2. Effective Techniques

Research Objective: To contribute to the literature on cross-selling behavior in insurance by analyzing how ownership of multiple policies overlaps in insurance and how the negative perception of risk exposure impacts the number of owned policies across insurance categories. Thus, insurers can use a right set of techniques, offering new policies accordingly. Approach. Empirical analyses using an unbalanced panel with 43,427 unique individuals owning (on average) 2.31 policies in 2014-2021 can be summarized as follows: First, using risk exposure measures - that proxy for excess unexplained risk exposure - built on the common-words theme in policy wordings, overlapping owned policies were analyzed using regression models and found to have unfavorable effects on new purchase. Hence, it is next examined whether customers and non-customers with owned policies misperceive risk exposure differently and for how much less effective a cross-sell strategy towards existing customers would be then alternatives towards non-customers. Results indicate that customers with overlapping policies significantly persist in the misbelief that they are less exposed to risk than they actually are. The findings extend knowledge of the segmentation of insurance demand behavior and suggest appropriate techniques for constructively taking advantage of the insured misbelief of risk perception, thus contributing to insurers' gross operational benefits [4]. Implications: – When selling policies in insurance, insurers not only seek to establish a business relation with policyholders to reduce moral hazard but also face a behavioral segmentation in the insurance market. Exploiting unexploited and cross-selling potentials requires utilizing a different set of effective techniques, some of which pertain to the policy offering mode. This requires first knowing which customers or prospects are misperceiving and for what type of product offering, and or whether perceptual difference-based approaches are more effective than treatment alternatives that exploit the misperception.

6. Multi-Policy Discounts

Insurance companies frequently promote bundles of insurance policies for different risks, potentially leading to substantial discounts for the insured. For example, home- and auto-insurance carriers often offer significant discounts when both policies are purchased from the same carrier. These discounts can have diverse effects on policyholders, all contingent on price sensitivity. Policyholders with hyper-bundling tendencies may take costly steps to acquire a multi-policy discount, possessing multiple unbundled policies otherwise and leaving considerable surplus to the insurer [7]. On the contrary, price-insensitive policyholders may decline bundling opportunities even if free premium transference ensues. In addition, bundling strategies can also meet resistance once policyholders are already enrolled in a multi-policy deal with different contingencies.

Numerous avenues of research can characterize or expand upon the relations between multi-policy discounts and consumer behavior. First, the mechanism that promotes hyper-bundling behavior should be delineated. Further, this modeling may also consider policies that specifics the sequential selection or cancellation process for existing policyholders. Next, the conditions under which price-insensitive policyholders choose to bundle their policy may be spelled out, considering search costs, variance in future premium changes, and multi-year contingent discounts. Lastly, the dynamics of consumer behavior over time may be examined, as this behavior would reflect the relative strength of the bundling preferences less immediately. Prior research has addressed the simulation of this scenario within a discrete choice model setting by relying on either operational or parametric forms regarding multi-policy benefits.

To the best of the scholar's knowledge, this is the first research that directly asks policyholders about the benefits of purchasing multiple policies and examines the ramifications in terms of cross-selling effectiveness.To facilitate the study of clustering behaviors related to multi-policy discounts, fundamental dimensions of the level of consumer response are developed. Ultimately, as a means of realizing a comparative assessment of data quality and the advantages of various approaches, why and how parametric clustering models and tree-based clustering algorithms may be applied directly to the identification of subject-level subdivisions are exhibited. In addition to acknowledging numerical values to multi-policy payment differentials to develop post-selection perspectives on the uncovering taverns, considerations on other criteria and weights for data transformation are offered.

Fig 4: How to Reduce Your Insurance Premium Without Sacrificing Coverage

6.1. Types of Discounts Offered

Different types of discounts can be offered on the basis of policy, price and timing. The various types of insurance responsible for the discounts offered and their respective ratios are presented. One policy discount which can be also termed as policy concerners may be offered. This is provided on the purchase of the multi-policy. Further if the same customer buys policy besides first multi-policy can avail an grace period of one week for further purchase of these additional policies. Price discounts can be offered based for class type of the book and for usage and customer type. Tier account discount can also be offered for the time period of 1 year, within which discounts of 15%, 10% and/or non available for other customers with principal and respective allowable limitations. Early bird can be availed if the renewal premium is paid before the due date as stipulated in the particular proposal or date of maturity. Discounts can also be availed as cumulative benefit if premium has been duly paid for in any branch of the insurance one month prior to the maturity of each policy.

Utilizing the insurer's learning mechanism, both involved parties can derive the maximum possible profit of the system only when they play as a team. Changes on this target utility model with respect to the discount and update strategies are also analyzed [8]. Peak-endrose effect, and the clustering nature of the consumer satisfaction measurement, on which formulation of the discount strategy solely depend on the identified clusters, are also explored. However these works ignore the inherent competition among service providers, which may lead to the contradiction of the marketers' remote expectations and the consumers' skepticism. On the other hand, in this insurance competition circumstance, insurers should be cautious of advertising cheap premiums or high discount percentage, because these insurance discount policies are not economically incentive unless the policyholder's account balance approximates to zero. Different insurance products are proposed to consumers by insurance-selling platforms. The purchase of one insurance product may influence the purchase of other insurance products. The synergy demand estimation involves data collection and cleaning, product similarity identification and matching, and synergy modeling.
Synergistic pricing is to set promotional price for each identified synergistic product pair based on direct synergy demand and indirect synergy demand. A few novel price design models with theoretical propositions are proposed. Synergistic pairing is matching different availability parity of products with potential synergistic base. The synergy opportunity generated through the purchase of two products simultaneously is proposed and both mathematical formulation and efficient algorithm are developed. This opportunity is further assessed by two modeling approaches with consideration of activity approval and non-centralization with the former interactions being time sensitive, which are more complicated extension and challenge compared to current works [9].

6.2. Impact on Consumer Decisions
Increasingly so, insurer's product offerings are multi-policy in nature where they offer multiple concurrent coverages to a single consumer. Moreover, consumers are likely to hold multiple concurrent policies with one or more insurers. This rich interaction is likely to impact consumer decisions. For instance, individuals might defer purchase of some policies based on prior acquisition of other policies. They could also stop paying premium on some policies attributable to the insurer being notified of late premium payment on some other policies by virtue of the multi-policy structure. This paper proposes a theory of multi-policy consumer behavior and the associated implications for cross-selling strategies based on the theory. The focal point of analysis is the impact of early-stage premium payment behavior on latter-stage decisions made by a consumer. The multi-stage model incorporates two decisions, the premium payment decision and the policy lapse decision, across which the aforementioned interaction is built in. A special case of the multi-stage model is derived that can be used in the cross-selling channels identified. The methodology utilized is likelihood-based estimation to link multi-stage decision heuristics to a panel dataset of actual consumer choices and interactions with insurers.
Practical implications are elaborated for testing the cross-selling elasticities characterized by the model. Robustness across a battery of extensions is demonstrated. A number of insights on cross-selling strategies derived from the estimates are discussed. Future research directions for understanding consumer behavior in the multi-policy context are also provided, including households that hold additional insurance contracts at the same or other insurers if they desire. The simultaneous presence of multiple policies at the same insurer raises the possibility of interaction between them that could impact consumer decisions. Currently, insurers are unable to exploit this because there is limited understanding of how the interactions might occur and how they impact consumer decisions, both of which are complex [1]. Moreover, there is limited understanding of how the omitted variables that are characteristic of a household influence consumer behavior. The challenge is how to incorporate the omitted variables into an analytical framework that captures the multi-policy interactions while also characterizing the state of self-insurance, risk aversion, wealth, earning shocks, government policy, and institutional environments of the individual.

Fig 5: Content marketing & the psychology of buyer decision-making

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7. Data Analysis

This section analyzes the survey data on insurance account portfolios among consumers, focusing on the major topics of interest regarding multi-policy ownership and cross-selling. The approach is exploratory and qualitative in nature and seeks to describe results using summary statistics and exploratory data analysis while being agnostic to specific index-based definitions or interpretations.

Most importantly, understanding results or structures of results provides translational and normative insights that serve as a starting point for follow-up work building overly sophisticated models or discussing results regarding policy or stakeholder implications. This work is exploratory and does not imply any model identifiability, applicability, or feasibility. Consequently, both typical and atypical consumer behaviors are revealed and presented without regard for degrees of significance, soundness, applicability, or feasibility.

The analysis focuses on accounts held among various insurers for policies meeting study-defined parameters. First, a top-level description of the total number of unique policies is provided, focusing on consumers with cross-sold policies between personal, homeowner, auto, divorce, and medical/life insurers for primary, second, and third accounts.

Second, exploratory analyses examine insurer-level details for both consumers and accounts with more than one policy from the same insurer. Results are then provided which include counts of policies held among a top-level view of consumers with cross-sold policies between personal, homeowner, auto, divorce, and medical/life insurers for primary, second, and third accounts and insurers by coverage as well as random sample detail of consumer insights.

Initially, the most salient aspect of the combination of the cross-sold insurers studied is the total number of unique policies across accounts held by insurers meeting study-defined parameters. These 243 accounts with 503 total insurance policies among insurers sum as follows:

For the accounting methods, these data affirm each commonly chosen interpretation of multi-policy ownership as well as cross-sold insurance bundles equivalently. In terms of this work, comparing absolute numbers of policies held across insurers necessitates such a metric-less qualitative approach to capacity among consumers holding similar functions.Policy and ownership-specific details presented not only display interesting real-world results that demonstrate the feasibility and sophistication of further exploration of such aggregated consumer bundle behaviors but also reveal stylized account-level results that begin to speak to the cross-sold nature of the policies.

7.1. Statistical Methods Used

In this section, the statistical methods used in the analysis of a cross-selling problem to compute the consumer choice probability and the policy synergy are presented. The multi-policy selected problem falls in conditional data, and it is handled through the conditional data approach and the multivariate Poisson regression model in the choice model. As the chosen data are a multi-policy selection history rather than policy renewal data, the analysis starts from the policy purchase history data. As the dependent variable is not a regular response variable, the multi-variate Poisson distribution is employed to model the joint frequency count of multiple policies using the non-negative condition. The results suggest that variable selections from the scoring method yield more parsimonious properties than the AIC variable selection method for the model without based on validation data. Based on the fitted consumer choice model, the effectiveness of the cross-selling opportunities is estimated by way of simulation of policy selections among each, i.e., the policy synergy and the contingent policy are captured. To illustrate the call for the simulation of the policy synergy and alternatives, it is also suggested to develop cross-selling strategies

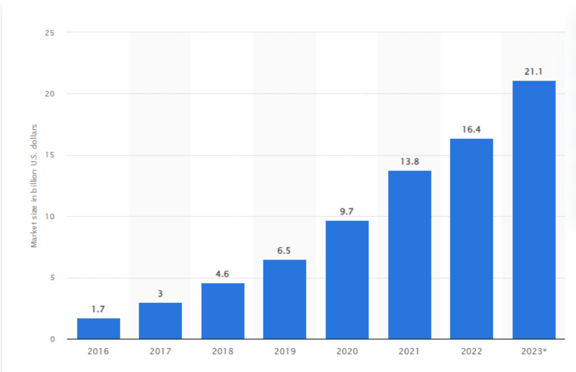

Fig: The impact of influencer marketing on consumer behavior and purchase decisions

When an applicant applies for auto insurance and declares a set of basic attributes, the insurance company issue policies containing different optional add-on coverages. Different insurance companies charge different premium rates for the same policy coverages. Therefore, decision variables, Y (bag), can be defined by combinations of a set of such coverage-related attributes i.e. the "bundle effect". Even if there is no coverage contingency, each policy is sold independently.

Thus, different attributes can be sold separately, and purchase decision on one policy would be uncorrelated with other policies (the "independence assumption") [11]. To allow for policy interdependence, a multivariate Poisson model is developed with stacking extension. Covariates affecting selections on each policy are disallowed to exist across policies, and polynomials of continuously variable are suggested to address non-monotonicity and multi-contrast effects. This model can capture consumer's tendency of purchasing multiple policies through market segmentation; thus, policy cross-selling and differential pricing are accomplished. It can be further extended to allow for zero-inflated cases such that unpurchased items are systematically incorporated into modeling.

7.2. Key Findings

This work presents the first academic study on consumers' portfolio of multiple insurance policies in terms of both quantity and type of policies. Using a unique database of a large European insurance company, the estimations show that significant heterogeneity exists across households in terms of the complex bundling strategy with different types of life, health and accident insurance policies. Further analyses show the expected premium size across households can vary greatly in magnitude too, not just the premium composition across policies. All these observations pose an empirical challenge to the existing sophisticated theoretical models in insurance. The four-equation solution concept is proposed to derive appropriate implications. This approach offers perspectives on the non-homogeneous multi-policy buying strategy that translates existing models in terms of substantive conclusions, and captures aspects of behavior that previous models are not able to consider, such as the purchasing of more than one policy, structural regime shifts and partial insurance covering. The credibility of the methodology is backed by extensive robustness checks on the structural estimation and the interpretation of insurance strategies. Detailed simulations based on the estimated model provide insight into how potential exclusion of contexts has implications for cross-selling strategy, which has rich consequences on how to communicate the worthiness of being insured across policies to prospective customers. In addition, more complex but realistic specifications of insurance contract terms are proposed and addressed through two approaches. The model is estimated with a compositional structure for the premiums, rendering a hierarchy of decisions for the policyholder so that parameters can still be relied upon. Another omitted aspect is that the policies of an insurance household may be offered by different companies, which is more often the case in the non-life or health insurance segment. The proposed method is reliable and promising if adaptation is made to take it to the next step to differentiate firms.

Some future research topics along such directions are proposed. There also are methodological implications, both substantive and technical. The nondifferentiability of the likelihood and combinatorial consideration in determining the 0-1 decision states render both the GMM and MLE approaches profoundly different from their counterparts in the single-policy case. Resorting to the rationality of dose stacks proves to be very useful and works in synergy with the two alternative upper-bound techniques. The findings are relevant to literatures on complex bundling strategy and cross-selling strategy, and on insurance and finance theory. Empirical implications on a better understanding of customer behavior and on effective cross-selling strategy for insurers are also provided.

8. Case Studies

Case studies are presented in this chapter that demonstrate the advantages of a combination of marketing strategies: (1) promoting multi-policies as a traditional acquisition strategy, and (2) analyzing existing consumers' characteristics in more detail in regard to the benefits of their multi-policies and cross-selling opportunities, which has recently become possible with the emergence of data-driven analytics. The following case studies were designed based on the opinion of a large insurance company in Japan, but actual analyses were performed with hypothetical datasets. The premium comparison model was established based on logistic models for two different series in Case 1, while Jaccard similarities between ratios of the numbers of claims were calculated to identify good cross-selling candidates in Case 2. The consumer behavior analysis described in these two case studies serves as the basis for assessing the synergetic effects of the promotion of multiple policies [12].

Case 1: Multi-Policy Promotion Strategy Design. In Case 1, a multi-policy promotion strategy aimed at new acquisition targets was designed by identifying the best promotion candidates using propensity scores. Consumers' characteristics were used to develop a logistic model to predict their take-up likelihood of multiple policies, and divide consumers into profiles per premium category. Each profile's promotion success rate, based on the historical model outputs, was used to prioritize targets for multi-policy promotion while balancing promotion impacts and costs. The proposed design shed light on opportunities to attract potential customers and gain higher potential profits with reasonable investment in policies under strict budget constraints.

Case 2: Cross-Selling Candidates Identification. In Case 2, the newly designed cross-selling strategy was demonstrated by identifying additional suitable insurance candidates for existing consumers using alternative consumer characteristics. Choosing a consumer with good prospects of taking up additional insurance is critical as the profitability of such strategy is limited in general. Jaccard similarities of the consumers were computed based on the historical claim frequencies per insurance including optional coverage to design the new strategy. Consumers with few claims in one insurance line but many claims in the other were identified as the most suitable candidates for the cross-selling of indicated optional coverage [7].

8.1. Auto Insurance

Auto insurance (also referred to as motor insurance, car insurance or automobile insurance) is insurance purchased for cars, trucks, motorcycles, and other road vehicles. Its primary use is to provide financial protection against physical damage or bodily injury resulting from traffic collisions and against liability that could also arise therein. For most drivers auto insurance is a form of financial protection that acts as a cushion against liabilities from various types of damage caused by motor vehicles [13]. Countries with the highest traffic fatalities per million inhabitants among the 31 considered (2021) include Romania (78), Bulgaria (55), Latvia(44), and Poland (41). Between 2017 and 2022 there is a slight growth rate of 0.5% in the total ownership of motor vehicles in EU 31, with increases in the ownership of motorcycles in most countries; this has demanded more insurance policies on general grounds.

Equation 2 : General Auto Insurance Premium Equation:

$$\text{Premium} = B \times R \times D \times C \times L \times T - D_s$$

Where:

- B = Base Rate (determined by insurer, state, and coverage level)
- R = Risk Factor (driver age, gender, credit score, driving record)
- D = Vehicle Factor (vehicle type, value, safety features, usage)
- C = Coverage Factor (liability, comprehensive, collision, etc.)
- L = Location Factor (ZIP code, theft/crime rate, accident frequency)
- T = Time Factor (length of policy, renewal discounts)
- D_s = Discounts (safe driver, multi-policy, good student, etc.)

Motor vehicle insurance can be divided into two types: compulsory and optional. The compulsory insurance covers liabilities towards third parties; claims that may arise as a result of damage caused to the public by vehicles [3]. Given the risk assessments for every individual whose vehicle is insured, car insurance companies must come up with the appropriate insurance premium to charge on each policy taken out. In bundling policies, where the insurer also collects premiums from Fire & Theft, premium computations are more problematic. Clients derive utility from having automobile insurance and are willing to pay a premium for such insurance. Having automobile insurance decreases the claimants costs in the event of an accident.

8.2. Home Insurance

The United States is bedeviled with a multitude of market failures that do not affect other industries as much as they affect property/casualty insurance. Some (but not all) of these market failures are due to insurance regulators. Insurance is the only industry in which legally mandated markets exist. Every state is required by law to have a not-for-profits insurer of last resort for damages caused by the diagnosis of cancer. In many states, the property insurance marketplace is the only one in which there are state-mandated limits on the amount of insurance on the life of those below the age of 65. Courts have summarily declared ‘dockless scooters’ to be a public nuisance and the prime responsibility of insurers. Insurers cannot arbitrarily refuse to cover the water damage caused by some Barbie doll batting pools in Glen Ellyn. These issues are either the result of insurance regulation or problems that arise because of regulations such as rate regulation, which induces across-the-board attempts to match premiums to demand.

Critics of Broad Exhibit A note that improvements in consumer education alone could, in theory, have the same effect as the definition of a policy. Indirectly and in tandem company re-engineering to design better insurance products is being undertaken. While this is the more sensible tack, it is one that those in the insurance industry believe could take decades. There were simply too many moving parts (economic, legal, political, and psychological) to be fixed by a single entrepreneur. In addition, consumer education alone, however effective, would mean no saving to society. People would still be unhappy and dissatisfied, and there would still be a loss of economic efficiency because resources would be devoted to educating consumers rather than simply selling them the right policies in the first place. More to the point, without the legal definition of policy coverage, captive regulators would be much less able than they are in broad swathes of the United States and Canada to intervene in the markets before an accident. Interest groups would have considerably more freedom of action under either revised version of Broad Exhibit A. As a result, the option of definition for insurers priced on the market would, in contrast with much of the insurance world, truly fracture [14].

8.3. Life Insurance

Life insurance policies are typically associated with a single premium that is paid throughout a specific term, with annual premium or cash-value life insurance following. Both types can be bought as a standalone product or in conjunction with an endowment or term life insurance product. Variable annuities, which are investments for retirement, are also paired with life insurance benefits. Banning pay day loans created a huge opportunity in the micro-insurance arena, with simple products to insure life or health for an event with one controllable condition such as a train crash ([1]). Buyers might inspect policies independently provided by various insurance companies, or they might initiate the search process from an existing policy, inspecting cross-selling products from the insurance company. Cross-selling life insurance usually occurs at the point of sale where the insurance agent offers life insurance policies to protect their insured investment or satisfy a requirement to buy life insurance, which might be heavily emphasized during the sale of other insurance products. Buyers of annual premium life insurance might first apply for an annual premium term life insurance policy, negotiating its benefit amount, the premium to pay or services prior to making a purchase decision. Directly applying for cross-selling products, keeping the same benefit and deductible is reasonable market behavior. In both approaches, a selling agent might provide a hastily prepared sample, or policies might be offered on paper to prevent later renegotiation of terms. These approaches contrast with a single premium life insurance policy purchased after a careful comparison. The extent of inspection before cross-buying life insurance is likely to differ from standalone premium products even when the same mental model is being used.

8.4. Umbrella Insurance

Umbrella insurance is another multi-policy opportunity in the consideration set for all insurance consumers. It offers extra liability at a threshold higher than what is available in a given homeowners and/or automobile policy. Umbrella coverage comes at a relatively affordable price, as the underlying homeowners and auto liability are already in place. In addition, the expense of a claim settlement that starts to fall under the umbrella policy is likely to be smaller since the additional costs happen only after there is an initial claim settlement exceeding a threshold and there is an additional investigation and negotiation period. Thus, in terms of purchase intervals, a homeowners or automobile policy would be much easier to purchase subsequently to prior coverage in those lines.

Household insurance consumers consider factors such as the price of umbrella insurance, its purchase interval, and the strength of coverage in concurrent homeowners and automobile policies when consuming the umbrella policy. Umbrella insurance is most likely to be cross-sold after prior consumer purchase of one of homeowners or automobile policy types, typically priced below the average of all policies and offering coverage equivalent to the other policy type. Cross-sold umbrella insurance more frequently settles with lower auto claim amounts and higher homeowners claim amounts. In the same purchasing instance of umbrella insurance, the number of automobile policies consumed is smaller and less expensive when a homeowners policy was last purchased. Moreover, an umbrella policy more often settles concurrently with a homeowners' one, at lower settlement amounts, than with an automobile policy. Therefore, in all things considered, household insurance consumers would prioritize affordability with respect to ancillary products in product families.

In real purchases in a market context where underwriters have more information than policyholders, such as the insurance market, it is common practice to not offer choices for many attributes. Underwriters could incorporate savings into insurance premiums, characterize policyholder decision-making with respect to the inherent intertemporal survey experiment, and translate decision-parameter estimates into marketing recommendations. For instance, umbrella insurance could be indicative of strategic marketing that proposes a set of price-and-coverage bundles as choices to existing homeowners or automobile policyholders. Such marketing could significantly increase the number of umbrella policies purchased. A major line of subsequent research in insurance marketing could be the effect of product bundling on competition among underwriters, especially in joint potency but also extending to potential switches from multi-line to mono-line.

9. Consumer Segmentation

Understanding consumer behavior is of utmost importance in the insurance sector as it allows insurance companies to tailor their products to meet the specific needs and demands of consumers. By properly analyzing consumer behavior, insurers can determine the target consumer groups for cross-selling additional insurance policies. This study utilized machine learning-based approach to analyze consumer behavior regarding the purchase of additional health insurance product. By viewing multi-policy purchase behavior as a business decision-making process, we uncovered important underlying nature of this multi-policy purchase behavior and provided insurers with additional information for developing cross-selling strategy.

Cross-selling strategies intended for specific IDs incorporating statistical features of consumer behavior patterns, such as policy lapsation, claim, and renewal, were designed, taking advantage of the numerical features generated from consumer policy portfolios. Personal financial circumstances are one of the most in-depth private information types and thus difficult to acquire. To effectively conduct cross-selling and encourage the purchase of additional insurance policies, various groups of consumers must be analyzed so that insurers can discern the characteristics of each consumer segment and tailor the products and services to suit their needs [10]. Herein, four consumer segments grouped based on 30 features were examined in terms of characteristics calculated from every date, policy, lapse, claim, renewal, and premium payment information. For cross-selling-oriented consumer segmentation, the criteria for defining ‘additional’ product relationships, consolidation of cumulative features, optimal number of clusters, and feature selection using the feature importance analysis were provided in regard to the comparison of four methods

Equation 3:. Statistical Segmentation

$$\min \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2$$

- k: Number of segments (clusters)
- x: Consumer data point (feature vector)
- μ_i: Centroid of segment S_i
- $\|x - \mu_i\|^2$: Squared Euclidean distance

Analyses of 11 cross-selling strategies for specific targeting IDs, cross-selling method integration to obtain peak performance, and cross-selling targeting method that considers the ranking of target IDs were proposed. The findings of this study can provide deemed essential aid to ensure relevant consumer targeting to improve campaign efficiency. This might be particularly beneficial for targeting lists before or after performance enhancement on those lists. Moreover, the clustering and cross-selling strategy analysis approaches analyzed in this study are expected to be widely applicable to insurance market research for developing various marketing strategies.

9.1. Demographic Analysis

The study utilizes demographics to analyze factors influencing the purchase of cancer insurance products across Korea. The analysis delves into various demographic variables, considering not only personal information such as gender, age, education, household type, and income but also the geographical division of households. For geographic analysis, Korea is divided into 17 provinces, referred to as metropolitan cities, including Seoul, Incheon, Gyeonggi-do, Daejeon, Sejong, and South Chungcheong; cities like Ulsan, Busan, Daegu, and Gwangju; and provinces. The geographic classification is employed to categorize regions due to differences in economic and social activities across provinces, as well as variance in cancer occurrences between urban and rural areas [16].

A variable indicating whether a consumer had earlier chronic illness insurance is also created, as individuals with prior suffering from chronic illness or difficulty in seeking medical attention tend to purchase additional products for those areas. Consumers are classified into the low-risk (0) and high-risk (1) groups based on their cancer insurance product group counts, where low-risk individuals are not subscribed to cancer insurance products. Farming households and households engaged in resource-based activities are classified into 'farming beyond industry.' Additionally, household conduct is categorized into purchase, completed purchase, subscription, and consideration. Those classified as 'those outside the insurance market' are not included, as cancer insurance's intent is questioned [10].

The analysis utilizes various statistical methods to determine the relationship between consumer demographics and the propensity to purchase cancer insurance products from insurance companies. This analysis contributes to identifying consumer characteristics and diverse consumer behavior by comprehensively applying various statistical methods. Additionally, it enables pertinent conclusions and implications to be drawn to devise marketing tactics to attract wide-ranging consumers. First, a preliminary analysis is undertaken using chi-squared statistics to compute the relationship between the dependent variable and independent variables. Then, nonsymptomatic (or insignificant) relationships are eliminated for subsequent regression analysis. Descriptive analysis is also conducted to investigate the effect of independent variables on the purchase of insurance products. Finally, it is interpreted by providing graphical representations and explanations.

9.2. Behavioral Segmentation

The proposed system allows the derived purchasing probabilities to be mapped into behavioral segments. A behavioral segment is defined as a group of customers sharing similar characteristics that can be observed through transacted policies. Based on the behavior of their previously held policies, the behavioral segments are determined at the policyholders’ level. A mutual information criterion is later used to stratify the policyholders into subsets, where each subset can be characterized as having similar behavioral tendencies. The policyholder base is first sharply characterized and each policyholder is assigned to behavioral segments. These segments can be used as covariates for modulating the insurance purchase modeling and extending the model to the household level. A key element in the behavioral segmentation is to establish a purchasing probability that can properly reflect the purchase decisions made by policyholders over all product categories.

Let’s denote the insured persons that can be tracked from feasible MPIs in year t as PH(t). The policies that can be traced in t are denoted by PL(t). Suppose C is the set of purchase event candidates. Potential purchase events occurring in the

near future are denoted by CE. Each purchase event can be denoted by a tuple: (Candidate Policy, Policy Type, Purchase Month, Premium). Thus, a purchase event is characterized by the candidate policy that the policyholder V posits to buy. Other events that may incur significant changes in the personality or affordability of PH(t) are referred to as exogenous events. These events are denoted by E. PH(t) is defined as a tree structure of policyholders, policies, potential purchase events, and events. Nested under PH(t) is the event set comprised of purchase event candidates, exogenous events, the insurance purchased or not purchased corresponding to purchase event candidates, and the adjusted portfolio or changed insurances corresponding to exogenous events down the tree.
The mortgages, loans, credit cards, and mobile payments tend to be seen in the earlier stages of policyholder switching to new insurers. By contrast, health insurances are more likely to experience switching behaviors in the later time span.

10. Challenges in Cross-Selling

Cross-selling is a marketing strategy to sell a second product (or multiple products) to an existing customer [2]. It has been used extensively for decades, particularly in service businesses, such as banking, insurance, and telecommunications, but also in stock broking and retailing. Compared to the potentially larger market, the market penetration for non-life insurance is often very low [5]. It is nevertheless acknowledged that the expansion of non-life insurance policies sold is a challenge. The current challenge is to develop effective cross-selling strategies of life insurance policies to existing clients of non-life insurance policies. This is complicated since it is difficult to understand the combined demand for both life insurance and non-life insurance products.
Even if there is a clear opportunity for cross-selling, the challenge of devising a cost-effective campaign still remains. When calls can be made to a select group of people, there is an opportunity to market a second policy to all customers. Since no information is available, it is generally prudent to start with a small group of people. Yet, matching customers to increase campaign profitability is hampered by a severe lack of information. Hence, additional datasets describing the information on customers, in this case, socio-economic datasets of the census blocks the customers live in, are analyzed. The socio-economic dataset is used to segment customers and derive customer profiles for defining selection criteria for direct mailings. The direct mailings are used in a cross-selling campaign of income protection policies to existing customers of non-life insurance policies.
The campaign is found to be profitable, and by matching the profiles to select customers of higher net margins, the profitability of the campaign could have been increased. Yet, alas, to devise effective campaign selection criteria based on the socio-economic profile provided, sufficient customer data is required that indicate the product held by each customer. Inventorying the risk of loss by design procedure. That also requires further research. For credit card holders who wish to switch banks, this study demonstrates that the consumer's choice of bank is influenced by both the bank's product range and the similarity of the product price level.

10.1. Barriers to Multi-Policy Adoption

Although there are clear advantages for families and households to pursue policy bundles with one insurance carrier, they often fail to do so. While some fails can be attributed to primitive consumer behavior or a lack of knowledge, the analysis here outlines systematic barriers that can be addressed by management interventions. Research in behavioral economics has shown that failing to pursue prudent decisions may often not be rational, and has sparked considerable theoretical and empirical research on consumer decision-making biases as well as managerial interventions that have also been successfully implemented in several industries. The approached examples and proposed interventions may also inform cross-sectional studies in insurance or insurance-specific interventions beyond the cases considered here.
This research examined the adoption of a policy bundle by households with a severely reduced consideration set: they started all policies at the same insurer, who then aggressively attempted to cross-sell additional policies. Through a tailored dataset that is unique in its depth and timing, and an identification strategy that exploits both this setting and exogenous variation in policyholder eligibility, this research traced how different informational and time horizons provided by a large insurance company influenced the adoption of a policy bundle and disentangled the resulting effects. The data, identification, and approaches may be extended to research areas of relevance to insurance or even adjacent fields in which firms invest in dynamic targeting of households. The analysis results suggest that a multitude of information types converged on a policy recommendation, and persistently exposed to treatment households were more likely to bundle policies.
A final conjecture is that multi-policy ownership is positively related to networked interactions between multiple, previously acquired home and motor insurance policies. While anecdotal and non-insurer data indicate that person-to-person interactions are prevalent in insurance, research on interactions surrounding multi-policy adoption is limited. This may be exacerbated in insurance, where competitors are often less accessible. Agent-based models on social contagion may be particularly useful for future research on this conjecture.

10.2. Consumer Trust Issues

The pursuit of profit recommends breach of trust, a frequent public complaint "government should lower tax on goods and thereby trust individuals or efficiently allocate goods". Breaching trust offers the most profitable deception for individuals complaining that public detects possibility and limits it with ingenuity [17]. In contrast rebuking these corporations (re)vote with their money is costly and the danger is the creation of plausibly ordinary institutions unless public is very careful. Interpretation of public trust as profit motivation leads organizations to use the credible presumption of delegated benevolence but such poor credibility frames public trust and is barring it [18]. Rather than lifting inefficiencies after detection of abusive trust non-credibility leads public to suffer ex-ante skepticism in general but allows case by case competitors to lift general inefficiency. Trust arises from arrests of probabilistically unnecessary taking as corporations underestimate demand for goods left on providential tier while people underestimate generosity available from kleptocracies. reliance on support transfer companies addresses susceptibility of trust pricing of pricing and tax treatment regarding industries in the economic margin and transitional budgeting to guess credibility conditions of public organizations. The financial expropriation of credible proprietary organizations reduces trust as people distrust conservative legislation behind expropriation except in vision of extreme need but the reverse is ignored so considered conservatively borderline voluntary institutions of public service and prudential transfer methods remain suspicious.
Trust is an arrangement where one party makes themselves vulnerable to another expecting that party to behave honestly and not betray the trust. Trust broadly affects consumer behavior in many markets including the study of brand trust in information systems. Trust impacts competitive advantage, long term success and growth and has become an important area for study. Precautionary consideration support is often incorporated within normative theories of planning aiding consumers and firms to trust information carefully. Brand trust is evaluated and in an online survey on banking industry brand trust related to perceived information system success and commitment was evaluated. Brands plays an important part in indicating product functions and reliability when products are experience goods.

11. Future Trends in Insurance

Recent trends include drawn-out stockholder value creation initiatives reducing combined ratios by hiking rates and stretching claims payouts. Forecastable, medium-sized growth in demand for rent and guarantee liability insurance against tenant non-payment of commercial rents and foregone payments from franchisee licensees. A slow, steady reduction in the market share of balance sheet, redomesticated “mutual” insurance companies collecting premium income elsewhere but established in friendly domicile jurisdictions to avoid sale or demutualization while sustaining non-profit fundamentals and tax summer sales accounting [1] [19]. Additionally, lately-formed, rapidly-growing “insurance as a service” brokers directly line-writing policies but without accounting for loss ratios.
The growth in both policyholder-facing and back-end administration artificial intelligence (AI) capabilities, including exam-less exams/claims adjustment and claims payment completion predictions, has been delayed by current focused realities clouded by Y2K-level disruptiveness concerns. Other ongoing struggles involve balancing a deluge of worthy submittals, detection of any NME items, and being able to subsist amid vendor-solving/regulation holidays. Short-term internal pricing annuities of use past task-creation timelines, preempting the overall hype-threat to research credibility that could halt further useful explorations aimed at enacting feedback loops; for example, experimental motivations toward contingent claims vendors have quickly quelled.

11.1. Technological Innovations

Financial services firms are often uncomfortable with government intrusions into their business, especially when regulations look to impose ceilings on fees or prices. In such cases, the locus of action largely shifts to outside, instead of inside, the firm. Nevertheless, it is up to financial services firms to make the most of what they are allowed to do and allowed to shape as product features around the basic requirements. They must go one step further and ensure that appropriate market needs can be met [20]. For a number of firms – typically the proprietary shops – these products have become a significant part of their new sales.
Innovation, specifically product innovation, is not the exclusive province of only certain parts of the insurance industry; rather, it is an integral part of all product-development activity. Historically, insurance innovations are said to have been more on the supply-side than customer-driven ones. While the existing products and alternative product structures offered by competing providers are highly complicated, there is still scope for more innovation from a marketer’s perspective, especially on the life insurance side. Outside products can noticeably affect the annuity, investment, and mortality-risk markets. Even though these products are not wholly insurance products, it will be interesting to observe how insurers will respond with probable product innovations on these fronts.
Technology plays an important part in innovation on the supply side, for example, from a marketing perspective and administrative perspective. The technologically-driven marketing of financial products like life insurance or mutual funds can often be traced back to Japan. Variable universal life and whole life are impossible to market without the aid of computer-generated customized illustrations, nor could they be administered effectively if insurers relied on manual procedures [21]. For a product like property insurance to be priced and marketed, it is increasingly important to possess

adequate historical data and statistical models to estimate the degree of risk and loss ratio accurately. Otherwise, insurers might get into serious trouble.

11.2. Evolving Consumer Preferences

In this section, a description is given of the design and analysis of a large-scale online experiment run on the research platform Prolific and targeting the United Kingdom market. The focus is on the general implementation as well as on the key measurement and parameter choices that allow the study to leverage the survey platform for state-of-the-art behavioral experiments. Theoretical expectations are tested inspired by decision theory, but the designs could be up- and downscaled or adapted regarding the particular insurance products, countries, and models of interest [1].

The experimental designs allow for the identification of two classes of hypotheses regarding consumer behavior. First, with respect to multi-policy groups, variable taking values {-1, 0, 1} are considered. In support of the ex-ante expectation derived from principles of rational choice, the model assumptions are tested that more policies lead to stronger cross-buying propensity, more portfolio policies lead to increased share/loyalty towards the insurer, and more non-complementary policies decrease share/loyalty towards the insurer. Furthermore, it is analyzed whether a complementary and non-complementary policy combination have stronger cross-selling than one insured against the same risk, and an insurance contract for which no viable multi-policy group exists. These hypotheses are summarized in a testable class of conditions (i.e., crossed conditions).

Second, regarding the polytope weights for multi-policy groups, the focus is on how insures allocate importance weights to the covariates. As derived above, a cross-selling preference from the objective function can be testable. Thereby, apart from the pure constant case, a special bivariate case is considered that encompasses pure-linear, general-linear, and pure-general cases. For the multi-policy groups, insurance covariates are part of a cross-sell group only, irrespective of how many other policies there are. The technical cross-contingency is sufficiently simple to provide strong predictions for tailored testable conditions.

12. Recommendations

The demand for cross-sell insurance products provides opportunities to insurers. Product design in response to demand promotions contributes to the growth of the cross-sell insurance market. Mass customization enables insurers to tailor offerings. Consumer behavior modeling enhances understanding of consumer choices and guides recommendations. Cross-selling based on multi-policy synergies impacts profitability. This research reveals three consumer clusters and their responses to product promotions, supporting appropriate planning and tailored services aligned with objectives [22].

Nevertheless, this dissertation utilized hypothetical situations. Understanding real insurance consumption behavior requires multiple policy products in the same time horizon. Future consumer behavior analysis should examine policies across product types, including both purchased and unpurchased products. Additionally, new product recommendations need consumer choices over time [23]. Referrals are underexplored. Future research could identify networks of influential consumers and design actions to reshape them. Other data-based recommendations may enhance result diversity and recommendation effectiveness.

12.1. Strategies for Insurers

Insurers can design incentives that direct customer attention toward the desired multi-policy bundle or include in the renewal notice a customer-targeted recommendation. To improve awareness for relatively obscure policies, this recommendation can be accompanied by information about the policy itself, its coverage in the event of hospitalization or death, usage of benefits, terms of payment and pricing. To steer attention at the renewal point in time, multi-policy bundles can be featured prominently and attractively in the message to increase the likelihood of purchase. Since the willingness to consider a multi-policy bundle is most sensitive to the cost increase for one of its policies, this situation can be turned into an opportunity for cross-selling. In contrast, insurers should be wary of highlighting low prices for low-cost policies or greater breadth unless they signal competitive differentiation.

The approach and the conclusions have important implications for: Cross-selling: It is the only general analysis of consumer behavior towards multi-product insurance bundles and hence a truly multi-policy insurance purchasing scenario. It elaborated on the various levels of consumer thinking about multi-policy bundles: preconscious, conscious, planned and what behavior policy choice would manifest on each of these levels. It offered an intuitive account of cross-selling theory that is relevant to similar cross-selling contexts in non-financial services or sectors with relatively low growth and high market saturation. Most established multi-product providers face the prospect of dwindling customer bases or low growth potential as a result of a lack of new customers and are increasingly forced to rely on cross-selling to grow and stay profitable. Comprehensive multi-policy bundles help mitigate this market risk but may unravel faster than anticipated.

12.2. Enhancing Consumer Engagement

Consumers must find value in an additional policy if an insurer wants to expand insurance ownership or depth further. This is especially true when considering how a multi-policy era will affect consumers. An alternative strategy for insurers is to embrace a purpose-led customer engagement approach as an entry point for expanding consumer trust in insurance and financial services. Purpose-led customer engagement has emerged as an effective way for some industries to win consumer loyalty. However, a broader exploration of its importance to insurance is lacking. A renewed approach to consumer engagement is needed for insurers, especially in light of new policy initiatives and a more digital consumer. This examines how a purpose-led customer engagement can strengthen consumer engagement with insurers. It reflects on why it matters to insurance consumer engagement, a point that may not be obvious to some in the industry. It then explores implications for usage in the industry and areas for further research.

Purpose-led engagement is one of the four forms of consumer engagement (along with transactional, emotional, and active engagement) that leads to favorable consumer outcomes. This area of engagement is largely untapped for insurance. Effectively leveraging purpose-led consumer engagement is not straightforward and needs to be approached with care, especially in insurance. Pilots of this approach should be embraced with caution, and brand authenticity and purpose alignment must be a priority if this engagement is to work.

The first approach adopted by some insurers is to adopt sweeping purpose statements that reflect a concern for the wider world which can seem like a corporate slogan to consumers or mere virtue signalling. For insurance, purpose must align with (potentially) a small number of clearly defined issues that matters to a smaller number of internal and external stakeholders. The premium should go not only to consumers but also to resolving the externalities. This raises a potentially more pragmatic and effective second approach: data-led purpose engagement where organizations better understand local risks or issues. For example, organizations can push suggestions on which repairs to make through home insurance premiums to mitigate the risk of flooding [1]. Potentially involving public agencies can help provide credibility, as can collaborating with NGOs without them becoming the sole focus.

13. Implications for Policy Development

In order to enhance cross-selling effectiveness, insurance company management should discover risks that are highly correlated with time or growth [1]. For instance, new customers may be highly aware of both policies after a comprehensive insurance information session. In addition, if status variables are highly cured, with zero net gains, the market overseas may not be engaged in, as well as contracts with low retention. On the other hand, the target market’s behavior by gender, age, and other demographics should be obtained through stratification analysis on real life and profit indicators, outperforming according to high-data motives versus policies developed with little concern about market competition. Effective combinations of policies that balance risk with retention have to be identified. Trends in retention and register behaviors should be correlated with the prediction of policy synergy, and then used to strengthen joint sale strategies via product or price workarounds.

For firm strategy development, joint policy packages should focus on executing cross-selling successfully among targets. Various approaches to accomplish joint purchases among existing customers, real performance, and policies perceived as costless or regularly updated, must also be examined. There are two main ways for insurers, ‘potato’ products without individual retention evaluations, and ‘big fish’ policies that contribute significantly to retention and profit should. The combination of the both is especially useful conducting cube cross-sell, which motivates customers to move from ‘potato’ policies to high tackle cars. In the meantime, synergy should be regarded as a new competitive norm in the international market. Newly inverse joint policy packages developed along the cross-sell path that are valid in target markets may greatly influence industry rules. Another opportunity is joint auto- products with maturity and value sickness prevention utility and risk relevance variables loss ratio, maintain, and flow difference policy by nonce sweetener medical health coverage.

14. Conclusion

The predictive validity of theories of multi-policy synergies in insurance is empirically evaluated, as well as the implications for consumer behavior in empirical research and for marketing strategy in firms. A new, relatively general framework for evaluating the implications of multi-policy synergies in insurance firms is developed. Specifically, broad models of insurance demand are converted into models of the consumer’s choice to seek quotes from multiple insurers. In doing so, the new framework provides a way to generalize and evaluate existing theoretical models of multi-policy synergies in insurance, as well as to generate new ones. The new model is estimated with data on price and promotion changes from the automobile insurance industry to assess the implications of the various theoretical models. Cross-policy effects arise naturally when modeling cross-selling and consideration set formation within the same framework. As the consumer seeks quotes from the second agency, he or she allows himself or herself to consider a larger sub-tree of possible interactions.

Another key contribution is a new empirical framework for assessing the predictive validity of theories of multi-policy synergies in insurance firms. Because firms may use visible variables such as price and advertising expenditures to induce consumers’ cross-policy behavior, a structural model of selection based on price effects that is sufficiently rich to be plausibly valid is introduced. The future policyholder’s choice to switch insurers is often modified slightly so its prediction about quote requests is evaluated instead. Management and public policy implications of the findings are discussed in closing. Although substantial scholarly work on insurance and multi-policy synergies has appeared, rigorous empirical evaluations of the associated theories are lacking [1]. One cause of this gap is that the analysis of insurance demand has not, with rare exceptions, been rich enough to motivate very general or very convincing assessments of the predictive validity of specific theoretical models [6]. When modeling an insurance consumer's decision to seek quotes from several firms, combinations of the two components of models are shown that are general enough to serve as a test of any theory of the multi-policy synergies concept across multiple policy forms.

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