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MARKOV CHAIN MODELLING OF PERSISTENCY FOR LIFE INSURANCE IN INDIA

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ABSTRACT: Life Insurance companies have been struggling with the challenge of low persistency, in India. Policies renewed every year are low in number. This indicates the loss of customer confidence in the corporation and misselling of products. To analyze policies statistically is important for devising strategies to increase persistency, which includes modelling of survival time of policy, identifying the grey areas in life insurance etc. In the present study, the cohort of policies procured in a certain year is assessed for status of each policy every year for the next three years after inception under the three broad types of insurance products: Term, Savings and Health insurance products. First order Markov Chain Model with three states: in force, critically lapsed and finally lapsed, is applied for each type of product. Probability of persistency for three - year period is also evaluated. All the products are found to be low probable for being in force yet health products have the least probability of the same. The similar result is obtained for revival of policies and the probability of persistency. For all the three types of products, the one step transition probability from state 2 to state 3 is estimated to be high.

1. INTRODUCTION

In Indian scenario, presently insurance companies are striving with the challenge of low persistency. The new policies are procured every year, but the old policies are not renewed at every due date of premium payment. The renewal ideally should be until the date of maturity of policy or until the happening of an event insured. However, policies renewed every year are very low in number. In fact, on the average 40% of the procured policies get lapsed during first year of policy after inception and out of the in-force policies at the end of first year, on the average 24% policies get lapsed. This is how percentage of retained policies gets reduced every year till the fifth policy year after inception in a policy year. The analysis of persistency during each year for next five years after inception, is based upon the experience of insurance companies which evidently support the fact that after five years the policy has maximum probability of getting renewed during entire premium paying term. The persistency evaluated for different portfolios of insurance products help only in assessing the fact that it is low in every portfolio. Similarly modeling the survival times of policies help in obtaining the best model for the same and assessing the nature of relationships between covariates & persistency. The models also help in forecasting of the hazard rate corresponding to the certain values of the independent criteria. But, application of suitable Markov model helps in assessing the transition probabilities from in force state to the state of critical lapsation or vice versa by revival of policy and from critical lapsation till the final lapsation that is when policy exits the books of insurance company. As per the amendments introduced by Insurance Regulatory and Development Authority of India (IRDAI) in insurance laws during 2014, if policy is lapsed for 2 years or more than 2 years, it cannot be revived and hence, exits the books of insurance company. Such Markov model also helps in obtaining the transition probabilities for different insurance products portfolios, to study them individually for identifying the low risk and high-risk portfolios. Previously many researchers have applied Markov models to different problems not necessarily the clinical trials. These areas include the Dynamic estimation of credit rating transition probabilities; estimation of transition probabilities for different levels of care that claimants are receiving in the business of Long term care insurance, examination of transition probabilities in a three-state illness death model without recovery, use of semi Markov models in the presence of left, right and interval censoring with piecewise constant hazards etc.

We are now giving brief overview of work done previously. Due to foreword of essential long-term care insurance in Germany, a large collection of data was available with a significant proportion of censored observations. Czado Rudolph [1] analyzed a part of this portfolio using the Cox Proportional hazard (CPH) model approach for estimating the transition intensities. Such an approach had also endorsed the insertion of censored observations as well as that of the time dependent risk factors. Then they employed these estimated transition intensities in a multiple state Markov process for calculating the premiums in LTC insurance plans. Arthur M Berd [2] presented a continuous time MLE methodology for credit rating transition probabilities, considering the censored data. They performed undulating estimates of the transition matrices with exponential time weighting with changing horizons and discussed the fundamental dynamics of transition generator matrices in short-term and long term estimation horizons. Daniel Commenges [3] had given the review of various approaches for estimation of transition intensities using maximum likelihood method. These include Homogeneous Markov models, non-parametric approaches to non-homogeneous Markov models which further may follow two paths: one implies a restriction to smooth intensities models, the other is the completely non-parametric approach and a generation of the Turnbull approach. Venediktos Kapetanakis et al [4] presented a parametric method of fitting the semi Markov models in the presence of left, right & interval censoring and with piecewise constant hazards. They explored transition intensities in a three-state illness death model without recovery. They tranquilled the Markov assumption by correcting the intensity for the transition from illness to death for the time spent in state illness through a time-varying covariate. This included the accurate time of the transition from healthy to state of illness. When the data were subject to left or interval censoring, the time was unidentified. In the estimation of the likelihood, they considered interval censoring by integrating out all possible times for the transition from healthy to illness state. For left censoring, they used an E-M inspired algorithm. A simulation study was carried to assess the performance of the method. The proposed combination of statistical procedures provided great flexibility. Mohd. Rahimie Bin Md. Noor and Zaidi Mat Isa [5] described the application of Markov chain as an approach for forecasting the buying patterns in life insurance. Their model used a sample of purchased life insurance from General Assurance Berhad for the period 2003-2006. The built Markov chain model is type of the first stage with a homogeneous time. This model used the idea of stop-motion to clarify the conditions of the time and number of purchase. At the end of the study, the Markov chain was established as a good method for predicting. A. S. Mac Donald [6] surveyed some statistical models of survival data. These included Markov, semi Markov, Poisson and traditional Binomial model. Poisson model was discussed as an approximation to the two state markov model. However, conventional binomial type models are proved less tractable than multiple state models and more restricted too. Torunn Heggland [7] studied three state illness death model with no recovery and considered two methods for estimation of transition probabilities under such model, in addition to the Aalen Johansen estimator. The first one is a method assuming that the data follow semi Markov property, while the other is a general method not built under any assumption. They established that Aalen Johansen works well only under the Markov assumption being true. The semi Markov method performs well only when the data are actually semi Markov. For general method they observed that approximately it provides unbiased estimators but with larger variances than under the two methods.

The Boston Consulting Group (BCG) and Federation of Indian Chambers of Commerce and Industry (FICCI)[8] illustrated in their report that by 2020, India will have maximum number of young individuals as working population. In the absence of social security system, these individuals will require life insurance for financial protection. The industry would be benefitted a lot when awareness among these millennials has been so spread that in the forthcoming years India becomes a country of all citizens being financially protected. But covering every individual with the life cover would not still favor the insurance companies completely until the efforts for spreading the awareness about life protection covers and efforts for retaining the customers are being made together. The switching over behavior of youth looking for next best alternative which saves time and money both, along with better after sales service, is responsible for low retention of customers. Possible factors for low retention and high-risk portfolios may be assessed analyzing the problem in different feasible ways statistically.

This paper deals with the study of application of Markov models in life insurance for assessing the transitions of policy status from one state to another. We have studied the Markov model for different portfolios of insurance products which broadly include the Savings, Term and Health products. Pension and Ulip products are not so popular thus we may afford not to study these portfolios in current research. Also, there is a problem of scanty data under these portfolios which does not facilitate analysis statistically, as these products are not sold to large group of individuals. We have used the three-state illness death model with recovery but no transition from alive to death state. This is little bit different from Chiang's illness death model [9] as it also includes the transition from alive to death, but our model does not, that is in our model we have transitions from alive to illness state and from illness to alive along with the third and last transition from illness to death. There is one more difference in our model from the usual illness death model that no policy can remain in illness state next year after a transition from alive to illness has already taken place for two years. It either transits back to alive state or to transit further to death. Our model is time homogeneous also. To estimate each element in transition probability matrix we make use of Kolmogorov forward differential equations. But, these transition probabilities have been expressed as the function of transition intensities which have been further estimated using maximum likelihood method. This method employs waiting times, which take in to account the effect of Type 1 censoring also. We have also specified the asymptotic distribution of estimators of different transition intensities. After estimating the transition intensities, we have calculated transition probabilities using Euler's method of approximation to Ordinary First Order Linear differential equations. We have studied the Markov models under each product type to assess the magnitude of transition probabilities and hence ascertain which type of products has more transitions to lapsation and have concluded that they may be categorized as high risk/Grey areas in life insurance.

2. DATA PREPARATION AND ASSUMPTIONS

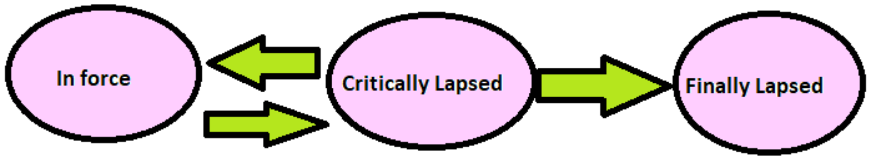
We have procured the data of 3663 policies collected from commercial sources of business lines and by surveying in Delhi NCR. Data consist of policies which were acquired during May 2014 –June2015 with a balanced mix of different areas of habitat; of various ages of policy holders, of several products offered by insurance companies like Term, Savings, ULIP, Health and Pension; of income levels, of sum assured etc. The categorical variables are coded appropriately according to each level of such variables. We assess the status of all policies in force exactly after one year only. So, in the study we have passed over the multiple transitions during any year from state 0 to state 1 or vice versa. That means we are considering the single transition from state 0 to state 1 or vice versa which is captured at the year - end only. This may be considered as limitation of the study but interim movements cannot be captured due to lack of robust systems capturing the live status of policies. Additionally, due to the provision for payment of premium during grace period of one month, policies with date of first unpaid premium in the months of May/June of any year have been supposed to be in force policies. We have further assumed that lapsation are concentrated during the mid of any year and the revival occurs at the end of the year.

3. EMPLOYED MODELS AND METHODOLOGY

We have applied the following Markov chain model (MCM):

Let X_t be the stochastic process with time $t >= 0$ and state space S = {In force, critically lapsed, Finally Lapsed} = {0,1,2} which is defined as the state of a policy at the time of assessment on yearly basis. A policy may be in: in force state, critically lapsed state and finally lapsed state.

The Transition Graph for X_t is given as follows:



In force {state 0}: policy is in force if it is renewed at every due date.

Critically lapsed {state 1}: if policy is lapsed for less than 2 years.

Finally lapsed {state 2}: if policy remains lapsed for 2 or more than 2 years.

Let initial probability vector be $q_0 = (1,0,0)$ which states that at time 0 that is when the policy has been procured it is always in the state of being in force because premium is always paid in advance.

Also, Let Transition Probability Matrix (TPM) P is given as:

$$\begin{array}{c c} & \begin{array}{ccc} 0 & 1 & 2 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \end{array} & \begin{pmatrix} p_{00} & p_{01} & 0 \\ p_{10} & 0 & p_{12} \\ 0 & 0 & 1 \end{pmatrix} \end{array}$$

A policy may remain in state 0 during the next year after inception, if it has been renewed and premium has been paid at every due date in first year. A policy may also transit to state1 during next year if premium has not been paid at any due date during the first year of policy. But there cannot be any movement in one step from state 0 to state 2. Similarly, a policy may transit from state 1 to state 0 if it has been revived within two years of lapsation. But, the same critically lapsed policy converts into finally lapsed policy and makes the transition from state 1 to state 2 if it is lapsed for 2 or more than 2 years. A policy, if enters in the state 2 must always be remained in the state of lapsation only. So, this state is an **absorbing state**.

To estimate the transition probabilities, we require introducing and employing the transition intensities corresponding to each state.

Let, $\lambda_{\alpha\beta}$ be the transition intensity of moving from state α to state β, then

$\lambda_{\alpha\beta} * \Delta + o(\Delta)$ = Pr [a policy in state α at time ξ will be in state β at time $\xi + \Delta$].

And, $\lambda_{\alpha\alpha} = -\sum_{\beta} \lambda_{\alpha\beta}$, for $\alpha \neq \beta$ which gives the following:

$1 + \lambda_{\alpha\alpha} * \Delta + o(\Delta)$ = Pr [a policy in state α at time ξ will remain in state α at time $\xi + \Delta$].

Now, the probability that policy is in state α at time t and shall move to state β at time ξ , symbolically, $P_{\alpha\beta}(t,\xi)$ is evaluated utilizing the Chapman Kolmogorov equations as given below:

$$P_{\alpha\beta}(t,\xi) = \sum_{\gamma} P_{\alpha\gamma}(t,\tau) * P_{\gamma\beta}(\tau,\xi) \ , \ \forall \gamma$$

Using these above-mentioned forms of equations for the states, 0 and 1, we find the **differential equations** as given below which help in obtaining the expression of Transition probabilities in terms of transition intensities.

The differential equations for $P_{\alpha\beta}(t,\xi)$ are obtained by considering the two contagious time intervals, (t,ξ) and $(\xi, \xi + \Delta)$, and the probabilities are given as follows:

For above TPM,

$P_{\overline{11}}(t,\xi) = 0$ and $P_{\overline{22}}(t,\xi) = 1$ where $P_{\overline{\alpha\alpha}}(t,\xi) =$ Pr[A policy is in state α at time t continuously remains in state α at time ξ].

But, $P_{\overline{00}}(t)$ may be evaluated as non – zero value using:

$$\frac{\partial}{\partial t} P_{\overline{00}}(t) = -P_{\overline{00}}(t) \sum_{j \neq 0} \lambda_{x+t}^{oj}$$

$$\Rightarrow \quad \frac{\frac{\partial}{\partial t} P_{\overline{00}}(t) = -P_{\overline{00}}(t) \sum_{j \neq 0} \lambda_{x+t}^{oj}}{P_{\overline{00}}(t)}$$

$$\Rightarrow \quad \frac{\partial}{\partial t} \log P_{\overline{00}}(t) = -\sum_{j \neq 0} \lambda_{x+t}^{0j}$$

Integrating both the sides with respect to t we get,

$$\Rightarrow \quad P_{\overline{00}}(t) = e^{-\int_0^t \sum_{j \neq 0} \lambda_{x+u}^{0j} du}$$

Also, since there does not exist any intermediate state between state 1 and state 2 for transiting from 1 to 2, therefore:

$$\Rightarrow \quad P_{12}(t) = e^{-\int_0^t \lambda_{x+u}^{12} du}$$

$$\Rightarrow \quad P_{12}(t) = e^{-\lambda_{12} t} \text{ and } P_{10}(t) = 1 - e^{-\lambda_{12} t}$$

Now, Considering Chapman Kolmogorov equations and taking in to consideration the two contagious time intervals (t,ξ) and (ξ,ξ+Δ), we obtain equations for rest two possible transition probabilities:

$$P_{00}(t, \xi + \Delta) = P_{00}(t, \xi)(1 + \lambda_{00}\Delta) + P_{01}(t, \xi)(\lambda_{10}\Delta) + O(\lambda)$$
$$P_{01}(t, \xi + \Delta) = P_{00}(t, \xi)(\lambda_{01}\Delta) + P_{01}(t, \xi)(1 + \lambda_{11}\Delta) + O(\lambda)$$

Which would further provide the differential equations as follows:

$$\frac{\partial}{\partial \xi} P_{00}(t, \xi) = P_{00}(t, \xi)(\lambda_{00}) + P_{01}(t, \xi)(\lambda_{10}) \text{ with initial condition}$$

$$P_{00}(t, t) = 1 \qquad (1)$$

$$\frac{\partial}{\partial \xi} P_{01}(t, \xi) = P_{00}(t, \xi)(\lambda_{01}) + P_{01}(t, \xi)(\lambda_{11}) \text{ with initial condition}$$

$$P_{01}(t, t) = 0 \qquad (2)$$

To solve the above equations (1) and (2) as a system of linear differential equations of first order we may apply Euler's method which is a numerical method giving approximate solution to ODEs.

Algorithm for the method:

If $\frac{dy}{dx} = f(x, y)$ with initial condition $y=y_0$ for $x = x_0$, then,

1) Replace f(x,y) by $f(x_0, y_0)$.
2) $Y_1=Y_0+(x_1-x_0)*f(x_0,y_0) = Y_0+h*f(x_0,y_0)+R$ for $x=x_1$ where R is the error due to approximation and is known as truncation error.
3) $Y_2=Y_1+h*f(x_1,y_1)$,......................................, $Y_{(n+1)} = Y_n+h*f(x_n,y_n)$. Thus, starting from x_0 when $y= y_0$ we construct a table of Y for given steps of h in x.

We shall now apply the above algorithm to the differential equations in 1,2→

In equation 1, $\frac{\partial}{\partial \xi} P_{00}(t,\xi) = P_{00}(t,\xi)(\lambda_{00}) + P_{01}(t,\xi)(\lambda_{10})$

$$\Rightarrow \quad \frac{\partial}{\partial \xi} P_{00}(t,\xi) = -(\lambda_{01}) * P_{00}(t,\xi) + \lambda_{10} * P_{01}(t,\xi)$$

Applying the above algorithm, we get,

$P_{00}^{h}(t,\xi) \cong P_{00}(t,\xi) + h*[P_{00}(t,\xi)*\{-(\lambda_{01})\} + \lambda_{10} * P_{01}(t,\xi)]$ at $\xi = t$,

$= 1 + h*[\{-(\lambda_{01})\} + 0*\lambda_{10}]$

$= 1 + h*\{-(\lambda_{01})\} \approx 1 - t*\lambda_{01}$

Similarly, at $\xi = t$

$P_{01}^{h}(t,\xi) \cong h*[\lambda_{01}]$ {since $P_{01}(t,t) = 0$ } $\approx t*\lambda_{01}$

But all these above transition probabilities are dependent upon the values of transition intensities which we also need to estimate. To estimate the transition intensities denoted as λ_{ij} , we have used the approach of Multiple state models as explained by Sverdrup [10] and Waters [11]. For the age interval t to t+1, the observations in respect of a single life are now:

1. The times between successive transitions and
2. The numbers of transitions of each type.

Since we have assumed initially that the transition intensities are time homogeneous and constants so it is sufficient to record the following:

V_i = waiting time of the ith life in the state of being in force.

W_i = waiting time of the ith life in the state of being critically lapsed.

S_i = number of transitions from in force to critically lapsed state.

R_i = number of transitions from critically lapsed to in force state.

U_i = number of transitions from critically lapsed to finally lapsed state.

Now we also define the totals as follows:

$$V = \sum_{i=1}^{N} V_i \text{ where N is the total number of lives in data.}$$

$$W = \sum_{i=1}^{N} W_i \quad , \ S = \sum_{i=1}^{N} S_i \ , \ R = \sum_{i=1}^{N} R_i \ , \ U = \sum_{i=1}^{N} U_i \ .$$

Using the Likelihood method, we have obtained:

$\hat{\lambda}_{01} = \frac{S}{V}$, $\hat{\lambda}_{10} = \frac{R}{W}$, $\hat{\lambda}_{12} = \frac{U}{W}$. All these estimators are asymptotically independent and the vector $\{\hat{\lambda}_{01}, \hat{\lambda}_{10}, \hat{\lambda}_{12}\}$ asymptotically has multivariate normal distribution and each component of it asymptotically has the marginal distribution which is Normal with parameters as follows:

$$\hat{\lambda}_{01} \sim N(\lambda_{01}, \frac{\lambda_{01}}{E(V)}), \ \hat{\lambda}_{10} \sim N(\lambda_{10}, \frac{\lambda_{10}}{E(W)}), \ \hat{\lambda}_{12} \sim N(\lambda_{12}, \frac{\lambda_{12}}{E(W)}).$$

Attaining the estimates of transition intensities, we put these in the expressions of transition probabilities to estimate the entries in TPM above. The estimation is done for all the three types of products that are savings, term and health insurance. For checking the validity of Markov chain model (MCM) of order one, we have applied two approaches: The Chi Square test for Goodness of Fit proposed by William P Lowry and Donald Guthrie [12] and the test for randomness of data proposed by Eggar[13].

In both approaches, the alternative hypothesis is same being MCM of order one is the best fit. However, both approaches have different null hypotheses. Goodness of fit test proposed by Lowry and Guthrie, tests the null hypothesis that the best fitted model is of order 0 and the approach proposed by Eggar, tests the null hypothesis for randomness of data. If the tests reject null hypotheses this implies that the fitted MCM of order one is a good fit.

Under the null hypotheses, both the approaches assumed chi square distribution of the test statistic with 4 degrees of freedom.

Throughout the study, *Excel* has been used for calculations.

4. Model Results

Since the MCM of order one is applied in the study, therefore, t =1 for TPM and is evaluated as given below. We have evaluated the TPM under broadly three categories of life insurance products namely: Health, Savings and Term insurance. We are exhibiting below the TPMs and the results of validity check under each category.

TPM under **Health Insurance**:

$$\begin{array}{cc} & \begin{array}{ccc} 0 & \quad 1 & \quad 2 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \end{array} & \begin{pmatrix} 0.418182 & 0.5818180 & 0 \\ 0.221199 & 0 & 0.778801 \\ 0 & 0 & 1 \end{pmatrix} \end{array}$$

To diagnostically check the validity of MCM of order one with the given TPM, we utilized the two approaches as mentioned above and then observed that

Approach 1:

H0: The MCM of order 0 is the best fit.

H1: The MCM of order 1 is the best fit.

We obtained the test statistic value

Chi square = 868.019 with p value = 0.00001 which is less than 0.01, the level of significance. Thus, it shows that there is sufficient evidence to reject the null hypothesis. So, MCM of order one is found to be the good fit.

Approach 2:

H0: There is randomness in the data.

H1: There is constancy in the data and MCM of order one is the good fit.

We obtained the test statistic value

Chi square =233.34 with p value = 0.00001 which is less than 0.01, the level of significance. Thus, it shows that there is sufficient evidence to reject the null hypothesis. So, the data are observed to be constant over the time regarding its behavior and MCM of order one is found to be the good fit.

Similarly, TPM under **Savings insurance**:

$$\begin{array}{c} \\ 0 \\ 1 \\ 2 \end{array} \begin{array}{c} \begin{array}{ccc} 0 & 1 & 2 \end{array} \\ \begin{pmatrix} 0.537828 & 0.4621720 & 0 \\ 0.216556 & 0 & 0.783444 \\ 0 & 0 & 1 \end{pmatrix} \end{array}$$

The tests for checking validity yielded the Chi square values 8698.54 and 1653.41 respectively with p value 0.00001 which supports rejection of null hypotheses in both the approaches. Therefore, it can be concluded that there is sufficient evidence to conclude that MCM of order one is a good fit, in case of savings insurance products as well.

And finally,TPM under **Term insurance**:

$$\begin{array}{c} \\ 0 \\ 1 \\ 2 \end{array} \begin{array}{c} \begin{array}{ccc} 0 & 1 & 2 \end{array} \\ \begin{pmatrix} 0.441544 & 0.5584560 & 0 \\ 0.226475 & 0 & 0.773525 \\ 0 & 0 & 1 \end{pmatrix} \end{array}$$

The tests for checking validity produced the Chi square values 1481.93 and 365.96 respectively with p value 0.00001which supports rejection of null hypotheses. Therefore, it can be concluded that there is sufficient evidence to conclude that MCM of order one is a good fit, in case of term insurance products too.

5. Discussions and conclusions

We witnessed that for health insurance products the probability for remaining in force is lowest among the three types of insurance products under study that is 0.418182. Then, the transition probability for moving from critically lapsed till finally lapsed is also very high being 0.778801. We have also computed the probability of persistency for 3 years' period standing at 0.174566, which is observed as the lowest among all the three products. Health insurance policies have lowest persistency for reasons, which are given below, and these are not the exhaustive list of probable factors for high lapsation but are major contributors towards lapsation. Health plans are majorly mis sold under the impression of Mediclaim which is a different product altogether. The major difference between the two is that Mediclaim restricts itself to the hospitalization expenses only. However, health insurance is a complete product. It offers an inclusive cover that extends further than hospitalization expenses and includes critical illness cover as well. But because a) the settlement of claim in Mediclaim policy is faster than that under health insurance policy b) in Mediclaim policy during the term of policy (generally one year) more than one claims may be made subject to the hospitalization of insured whereas in health insurance claim can be made only once at the happening of insured event and then after settlement of claim, the cover under the same policy ceases. That is why people prefer mediclaim policy more, over health insurance. While it is difficult to quantify the effect of mis-selling on an insurance company's valuation, it does get affected badly. High lapsation rate, which could be partially due to mis-selling of products, can be a drag on insurers' valuations. Other major reasons are poor servicing, fake policies and complexity of the system. Due to low premium in health insurance, the commission paid to agents is low and hence they are discouraged to provide services that meet customer's expectation. In fact, due to the low premium payable in health policies, it is not the area focused upon by insurer for capturing fraudulent activities of agents in case of bogus policies. Since health policies for life insurance companies are not engrossed upon due to low income from such policies therefore it becomes easy for agents/advisors to make bogus policies in the names of persons who do not even exist.

In case of savings products, the transition probability of being in force is highest being 0.537828. But the probability of transiting from state 1 to state 2 is also highest being 0.783444 which also raises concern. The probability of persistency for 3 years' period is also evaluated as 0.249945 which is quite low. Major oneof the probable reasons for low persistency in savings insurance products is as follows: people in our country generally do not realize the importance of providing benefit of insurance for payment at the event of death that is risk cover in savings products. They also compare savings insurance with other saving instruments available in the market which offer higher returns than insurance products but such products do not have risk cover. Insurance companies more prudently invest majorly into low to medium risk assets keeping reserves as well, to be solvent and liquid. So, insurance products do not provide high returns like other riskier investments may be offering. Also, benefit illustrations in these type of products does not provide IRR for surrenders. In such case, people do not get these policies surrendered as well rather policies get lapsed.

Examining the results for Term insurance, we again perceive the same problem of low chances of persistency for the three - year period being 0.187239. The one step transition probabilities from state 0 to state 0 and from state 1 to state 2 are 0.441544 and 0.773525 respectively. The latter implies that the chance of being finally lapsed when policy has already been lapsed critically is higher. This further means that a policy if gets lapsed then the revival of it is least probable. Term insurance products are generally lapsed by healthy persons in young ages. Investment in term insurance by this group of people is considered as the useless investment. Such products provide 100 per cent risk cover and takes in to consideration the mortality which varies by gender, but the same premium rates apply to both the female and male lives. Appropriately, such product design should be prepared which discriminates between the premium rates by gender also. So that lesser premium rates may be offered to the gender which experience better mortality.

Overall examining the results, we may conclude that health insurance is the greyest area to be focused upon. Although, every insurance product is suffering from the problem of low persistency hence, we may also conclude that entire insurance sector is suffering from the problem of low persistency. So, far in the present study we have evaluated under three types of insurance products, the probabilities of being in force, being persistent for three years' period, for transiting from critically lapsed state till finally lapsed and for revivals using Markov Chain model of order one which is also found to be valid in our case as per the tests applied. Study may be extended to identify the probable reasons for lapsation of insurance policies with the magnitude of impact and nature of relationship of these factors with the survival time of policy so that controlling measures may be taken appropriately thereby increasing persistency.

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