# The Effect of Risk Aversion on Lapsation in Iran Life Insurance Market

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## Abstract

*Adverse selection is a real obstacle in the life insurance industry describing a situation in which information asymmetry leads riskier policyholders to purchase more insurance coverage. Such kind of adverse selection is static adverse selection in the time of purchasing policy. Asymmetric information results in another type of adverse selection called dynamic adverse selection. Dynamic adverse selection occurs when individuals with high level of risk aversion (low-risk individuals) lapse a policy during the period of contract. Inversely, dynamic advantageous selection occurs when individuals with low level of risk aversion (high-risk individuals) lapse their contracts when policy is effective.*

*In this article, we investigate the effects of Risk Aversion on the lapsation of life insurance policies in Iranian Life Insurance Market. A Binary logistic analysis is used to examine the effects of risk aversion on lapsation of life insurance policies.*

*Results show that the lapsation of life insurance policies has a negative correlation with the risk aversion level of policyholders. Age, gender and marital status as risk aversion proxies affect significantly the lapsation of life insurance policies. Since individuals with low level of risk aversion (high-risk individuals) lapse their contracts more than individuals with high level of risk aversion (low-risk individuals), dynamic Advantageous Selection is evident in Iranian life Insurance Market.*

**Keywords:** *Dynamic Advantageous Selection, Dynamic Adverse Selection, Lapsation, and Risk Aversion.*

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## 1. Introduction

It is definitely necessary to understand the concept and behavior of lapsation and its determinants for insurance managers, regulators, and customers. For insurance managers, the profitability and liquidity of insurers can be increasingly influenced by lapses through costs, adverse selection, and cash surrender values. Therefore, lapse is a material risk for life insurance companies, which needs to be studied, controlled and managed carefully and strictly (Dieter Kiesenbauer, 2009)

Although both terms, lapse and surrender, refer to the termination of an insurance contract before maturity, there is a slight difference (see, e.g., Gatzert et al. 2009; Kuo et al. 2003). Whereas lapse refers to the termination of policies without payout to policyholders, surrender is used in cases where a cash surrender value is paid out to the policyholder. The term ‘‘lapse’’ refers to both surrender and lapse throughout this paper.

Losses incurred by lapses can be high for front-loaded contracts without surrender value. This is the case for most LTC policies, and motivates an analysis of lapse behavior. The average lapse rate of LTC contracts stands at 7% in the US (Society of Actuaries, 2002). So estimation/ study of lapse rates is useful for i) pricing the insurance products, ii) valuation of insurance liabilities, iii) comparison of experience with other countries, iv) benchmarking industry lapse rate, v) background information in product development, vi) identification of changing needs of the insured public, and vii) identifying the factors influencing the lapse rates and hence the changes required in various pricing parameters including marketing strategies (R. Kannan et. al. 2008).

As we know adverse selection is a real obstacle in the life insurance industry describing a situation in which information asymmetry leads riskier policyholders to purchase more insurance coverage. We can call such kind of adverse selection, static adverse selection in the time of purchasing policy. Asymmetric information has another result after passing a period of time, called dynamic adverse selection. Such kind of dynamic adverse selection says that lower-risk individuals are more likely to cancel a policy.

In this paper we are going to answer a very important question. It seems that lots of factors such as age at entry, mode of A.P payment, type of insurance, level of income, marital status, education, occupation, sex of individuals and even economic factors such as inflation rate, employment, returns of other investment tools etc. are the most significant factors affecting the lapse rate and most of these factors are related to customer's risk aversion / level of risk. For example, younger policyholders probably due to smaller and more uncertain income levels and low level of risk aversion tend to cancel more policies, or married policyholders, because of family protection and their family futures are reluctant to cancel their life insurance policies, and it is known that low-risk individuals are also more risk averse. Now how can we combine these tow conflict results? Are risk averse/low risk individuals more likely to lapse their life insurance contracts (dynamic adverse selection) or less likely to lapse (dynamic advantageous selection)?

Risk Aversion means a willingness to pay to eliminate risk. If it is assumed that the low-risk individuals are also sufficiently risk averse, they will value insurance so highly that it will be worthwhile for them to buy it even at a price higher than their actuarial fair rates ( Mahdavi and Backshi, 2011). We also know that Risk Aversion of individuals is affected by their age, sex, income, wealth, occupation, current health status etc. As a result, determining the Risk Aversion level of customers and existence of Dynamic Adverse Selection/ Dynamic Advantageous Selection in the life insurance market leads to life insurance companies insightful considerations regarding their financial circumstances.

We follow two main objectives in this research:

1. Determining the degree of correlation between Risk Aversion proxies and the lapsation of life insurance.
2. Examining the existence of Dynamic Adverse Selection or Dynamic Advantageous Selection in Iran life insurance market.

By applying Logistic Model, we estimated the relationship between Risk Aversion and the parameters of the lapsation of life insurance. We examined whether the independent variables of risk aversion

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parameters (xi) have significant effect on the dependent variable (Yi) (the lapsation of life insurance).

The null hypothesis of $H_0$: $\beta=٠$ states that the risk aversion level of individuals doesn't have a significant effect on the lapsation of life insurance. We also examined the existence of Dynamic Adverse Selection in Iran Life Insurance Market. In fact, when the low risk individuals (individuals with high level of risk aversion) lapse more life insurance services than the high risk individuals, Dynamic Adverse Selection will occur in Insurance Market; vice versa, when high risk individuals lapse more life insurance services than the low risk individuals (individuals with higher level of risk aversion), Dynamic Advantageous Selection will occur in Life Insurance Market.

In this paper, we drew data from Ma and Saman insurance companies, and assumed these two companies as a blended company.

The remainder of this paper is organized as follows:

- Chapter 2 delivers the empirical literature.
- Chapter 3 describes the data and variables and logistic model.
- Chapter 4 performs the empirical analysis, explains the test in detail.
- Chapter 5 provides the conclusion.

# Literature Review

We know that an important consequence of asymmetric information among consumers and insurers is adverse selection. Although we see a high number of empirical studies examining adverse selection (static adverse selection), there is not enough substantial empirical literature examining dynamic adverse/ advantageous selection in insurance markets. We briefly summarize literatures on Risk Aversion, Adverse Selection, Dynamic Adverse Selection and Lapsation.

Despite this straightforward understanding from the conventional theory of insurance demand under asymmetric information, this theory is not supported by most of the empirical works. There are many empirical evidences that appear to conflict with the standard theory of adverse selection in insurance market.

Chiappori and Salanié (2000) showed that when observationally identical individuals are offered a choice from the same menu of insurance contracts, higher risk individuals will buy more insurance. The intuition is straightforward. Since, at a given price, the marginal utility of insurance increases in risk type, higher risk individuals will choose to purchase more insurance than lower risk individuals who face the same set of options. Of course, this prediction, and any empirical test based on it, applies conditionally on the characteristics of the individual observed by the insurance company and used in setting insurance prices. Chiappori (2000) provides a survey of the existing empirical studies that have implemented this test for asymmetric information.

Meza and Webb (2001) stated that in addition to precautionary effect that explains the negative correlation between insurance demand and risk level, heterogeneous optimism also supports this negative correlation: high risks are more optimistic about the events to be improbable, so they purchase less insurance. Makki and Somwaru (2001) analyze farmer's choices of crop insurance contracts. Their analysis offers empirical evidence of adverse selection by showing that high-risk farmers are more likely to select revenue insurance contracts and higher coverage levels. Dachraoui, Dionne, Eeckhoudt and Godfroid (2004) showed that more risk averse agent whose behavior follows the mixed risk aversion utility function may spend more self-protection activities when the loss probabilities are below 1/2. Sigelman (2004) claims that the information asymmetries are in the favor of insurers not policyholders, as insurers utilize various strategies of underwriting and risk classification that compensate for or even overcome the informational advantage of the policyholders. Moreover, the behavioral or psychological factors help to offset insured's informational advantages.

Mahdavi and Rinaz (2005) investigated the demand for and pricing of life insurance when insured's risk aversion is correlated with their precautionary effort. They assumed that the population is divided into two groups: (i) very risk-averse individuals who have a low probability of death (POD) because of the precautionary effort they undertake, and (ii) less risk averse individuals who undertake less effort and thus have a higher POD. After computing the pooling equilibrium price under perfect competition for a class of CRRA3 utility and bequest functions, they computed the level of demand for life insurance by the two groups. Under the assumption of negative correlation between risk aversion and risk exposure, lower-risk individuals still buy insurance even if the price offered is higher than the fair price corresponding to their group. This is because low-risk individuals are assumed to be more risk averse, valuing insurance so highly that they can tolerate higher than fair prices. They also present some cases when low-risk individuals purchase more than their high-risk neighbors even though they realize they are subsidizing the high risks. In such cases, the insurers gain the advantage of facing a POD which is smaller than the rate they normally expect. This fact contradicts the so-called adverse selection hypothesis.

Ghadir Mahdavi (2006), found that under certain circumstances when the individuals are sufficiently risk averse, the probability of death is smaller than its critical value, and the processing cost is sufficiently large, the selection effect will be advantageous to the market. He also showed that when individuals are not sufficiently risk averse, and consequently their probability of death is not sufficiently small, the necessary condition for having advantageous selection regime is the processing cost to be smaller than its critical value.

Ghadir Mahdavi and Fatemeh Bakhshi(2011) investigated the effects of risk aversion on the demand for life insurance in Iran Life Insurance Market. They concluded that consumers who are willing to buy life insurance are more risk averse and have a lower risk level and the demand for life insurance has a positive correlation with the risk aversion. Since the individuals with high level of Risk Aversion (but with low level of risk) demand more life insurance rather than the individuals with high level of risk, we conclude that adverse selection doesn’t exist in Iran Life Insurance Market.

Above mentioned papers all discussed the effect of risk aversion level of individuals on the demand for insurance and the existence of adverse selection or advantageous selection in insurance market, but the presence of dynamic selection has, however, rarely been empirically explored. One of the few exceptions is Finkelstein et al.

(2005) examination of lapse behavior and ex-post nursing home utilization in the long-term care insurance market.

Daifeng He (2011) proved that life insurance market is faced with dynamic adverse selection. Using data from the Health and Retirement Study (HRS), he examined whether dynamic selection is present in the life insurance market. He found that individuals with lower mortality risk are more likely to lapse a contract than those with higher mortality risk, and that conditional on lapsation, lower-risk individuals appear to lapse policies of greater face value than do higher-risk individuals.

Lapse has been an area of intense academic interest since 1970s, but empirical studies are limited to a few countries and factors. Kim (2005) provides the first empirical study considering a broader range of explanatory variables. Kim (2005) considers economic variables as determinants for lapses as well as policyholder information on policy age since inception. Kim employs logistic regression models to identify lapse drivers and to develop a predictive lapse model using Korean data. Recent studies include Cerchiara et al. (2008) studying Italian data, and Spanish data are analyzed in Milhaud et al. (2010). Besides these empirical studies, different theoretical lapse rate models have been discussed, such as Kolkiewicz and Tan (2006) or Kochanski (2010). We briefly summarize some of them:

Martin Eling, Dieter Kiesenbauer (2011) considering the largest dataset ever used for this purpose (2.5 million contracts, 8.9 million policy years), analyzed the impact of product and policyholder characteristics on lapse in the German life insurance market. The sample period covers two periods of market turmoil that they incorporated in their generalized linear models. The results show that product characteristics such as product type or contract age and policyholder characteristics such as age or gender are important drivers for lapse rates. Their findings improve the understanding of lapse drivers and might be used by insurance managers and regulators for value and risk based management.

Kiesenbauer (2010) studied the determinants of lapse in the German life insurance industry. Logistic regression models are employed using data on macroeconomic indicators and company characteristics of 133 German life insurers from 1997 to 2009. Five different product categories are considered: endowment, annuity, term life, group, and other. The findings indicate that the main lapse determinants are very similar across all product categories, except that the direction of impact is reversed for the product category ‘‘other,’’ which consists almost exclusively of unit linked business. In particular, the interest rate and emergency fund hypotheses are supported only for unit-linked business, while these hypotheses do not hold for the remaining product categories.

Overall, the analysis provides an understanding of lapse dynamics related to economic indicators and company characteristics. The derived models can be used to predict lapse rates for the different product categories considered. The results are important for insurance company managers, regulators, and life insurance customers.

R. Kannan et al. (2008), in their complete research analyzed lapsation in the life insurance industry in India during 2002-03 to 2006-07 for individual life policies. They found that over the five years of investigation period, industry lapse rate with respect to number of policies increased from 5.62% (2002-03) to 7.8% (2004-05) and decreased to 6.64% (2006-07). Age at entry, mode of A.P payment, duration elapsed since policy inception, policy type and type of underwriting are found to be the most significant factors affecting the lapse rates, and whole life products showed higher lapse rate than endowment products for with-profit policies and the converse is observed for non-profit policies.

Jean Pinquet et al. provided empirical evidence on the lapse behavior. They found that policyholders who cancel their contract have good health histories compared to those of their peers, and that the lapse rate decreases with age, with a local peak at the age of 65. They argued that lapsation of young policyholders as well as that of elderly policyholders at retirement is partly due to a misunderstanding of the contract. They also discussed the fact that the portfolio avoids the "death spiral" that might have been expected after the run-off decision taken in 1997, caused by the continuous departure of the youngest policyholders. Based on this case study, they believed that insufficient knowledge of insurance products can cause lapsation which is detrimental to policyholders if triggered by information available at the date of purchase. Enhancing knowledge of the environment in terms of risk and insurance solutions would be welfare improving.

Kumar (2009) believes that early lapses pose a major financial problem to the life insurer. It has been realized that the phenomenon is not amenable to any simple statistical model due to an inherent stratification in the population of lapsed policies. Life insurers may have to adopt a uniform definition for lapsation of insurance policies to give more leeway to policyholders on A.P payments.

# Methodology

We apply the Logistic Model to examine the existence of adverse selection in Life Insurance Market. This model is often used when the object of the study is to model the probability of an event. Data are drawn from files of Ma and Saman insurance companies. Since there are qualitative data (sex, marital status, occupation, education, etc.), the Logistic Model will be an appropriate method to estimate our parameters ($\beta_i$):

$$Y_i=\mathrm{Logit}[\pi(x_i)] = \log (p_i/1-p_i) = \alpha + \beta X_i \quad ; i =1,2, \dots , n \qquad (1)$$

The model defines a relationship between the dependent variable ($Y_i$ lapsation of life insurance) and the characteristics of individuals ($x_i$) such as age, occupation, sex, etc.

- $Y_i^*$ shows the lapsation of life insurance. $P_i=y_i/n$ and $y_i$ can take two amounts:
- y is equal to 1 if the individuals lapse life insurance ($p_i= \pi(x_i)$).
- y is equal to 0 if the individuals don't lapse life insurance ($p_i=1-\pi(x_i)$).
- n is the number of policyholders.
- $\pi(x_i)$ is the probability of lapsation of life insurance. ($y_i=1$, $p_i=\pi(x_i)$)
- $x_i$ is an independent variable and shows the characteristics of policyholders such as age, gender, marital status, etc.
- $\alpha$ denotes the intercept of the equation.
- $\beta$ is the coefficient of independent variables xi. It shows the degree of correlation between the characteristics of individuals

who cancel life insurance (xi) (or risk aversion level of individuals) and the lapsation of the life insurance contract ($Y_i^*$).
The Logistic Model can be generalized directly to the situation where we have several predictor variables. So, we have:

$$\Pr (y = ١ \mid X_١ = x_١, X_٢ = x_2, \ldots, X_n = x_n) = \frac{e^{a+\beta 1x1+\ldots\ldots\beta ixi}}{1+e^{a+\beta 1x1+\ldots\ldots\beta ixi}} = \pi(x_i) \quad (2)$$

Equation 2 is non-linear in the parameters $\beta_٠$, $\beta_1$, …, $\beta_n$; however, it can be linear by the logarithmic transformation. We obtain the equation 2,

$$Y_i^* = \mathrm{Logit}(\pi(x_i)) = \mathrm{Log}(\pi(x_i)/1 - \pi(x_i)) = a + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i \quad (3)$$

**Maximum Likelihood Analysis**

Since our data follow a binomial distribution (because the individuals either demand life insurance or not), we apply maximum likelihood analysis using the binomial likelihood with mean value given by an appropriate function of predictors.
It can be written as:

$$\mathrm{Ln}(\pi(x_i)) = \alpha + \Sigma_i = 1,\ldots,n \ \{ y_i \log(\pi_i/1-\pi_i) + n_i \log(1-\pi_i)\} \quad (4)$$

We examine whether the independent variables ($x_i$) have significant effect on the dependent variable ($Y_i^*$) or not. $H_٠$: $\beta=0$ states that the $Y_i^*$ (dependent variable) is independent of xi (independent variable) or the lapsation of life insurance doesn't have a correlation with the characteristics of individuals who cancel their life insurance. We also use the statistical tests, Likelihood-ratio and Wald tests for determining the effectiveness.
Likelihood-ratio test statistic can be examined by:

$$\text{LR statistic} = -2 (\log (L_0) - \log (L_1)) \quad (5)$$

Where;
$L_٠$: is the maximized value of the likelihood function for the simpler model that assumes the null hypothesis.

$L_1$: is the maximized value of the likelihood function for the model. The obtained statistic is compared to the $\chi^2$ distribution.

Dynamic Advantageous selection exists in Life Insurance Market when the individuals with high level of risk aversion (in other words, low risk individuals) cancel more of life insurance services than the individuals with high risk individuals; vice versa, when the high risk individuals cancel more of life insurance services than the low risk individuals (in other words, individuals with higher level of risk aversion), Dynamic Adverse Selection will occur in Life Insurance Market.

# Results

About 4% of our randomly selected policies were lapsed during 2008 to 2013. Seventy five percent of our policyholders are under 35 years old and this amount is 32, conditionally on lapsation. Over 90% of lapsed policies were issued to policyholders that are under 35. Over 40% of policyholders are highly educated and this amount is nearly the same conditionally on lapsation. Respectively, 58.7% and 69.3% of policyholders are male and married and these amounts are 81% and 40.5%, conditionally on lapsation. These results are shown in details, in appendix, tables 1 and 2.

We examined whether the independent variables ($x_i$) have significant effect on the dependent variable ($\mathbf{Y_i}$). Since the null hypothesis of $H_0$: $\beta=0$ is rejected, we conclude that life insurance lapsation has a positive correlation with risk aversion level proxies such as age, occupation, sex, etc.

We estimated binary logistic regression using SPSS software.

Table 3 shows the probability of lapsation. According to this estimated regression the probability of lapsation is 0.042.

We see Omnibus Tests of Model Coefficients in table 4. P-value is equal to 0 and it shows that the regression is significant.

Tables 5 and 6 indicate that Cox & Snell and Nagelkerke R Square are 0.181 and 0.628, respectively and Overall Percentage Correct is

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97.5 percent. In addition, this model can predict the probability of lapsation with a probability of 0.458.

We used the Wald test to examine the statistical significance of each coefficient in the model. A Wald test calculates a **Z** statistic. The value of this statistic is obtained from Binary Logistic results.
In Table 7 we can clearly observe that null hypothesis $\beta_i=0$ is not rejected for the education variable at 0.05 confidence interval level and for the age variable at 0.01. So we can conclude that:

1. Null hypothesis $\beta_i=0$ is rejected for the education variable at 0.05 level stating that this variable has no effect on lapsation of life insurance policies.
2. We have no evidence to reject null hypothesis $\beta_i=0$ for some variables such as Gender, M.S (marital status), Age, C.R (clinical rate), P.P (policy period), N.I (number of installments), Amount of premium (A.P) and Initial face amount (I.F.A) stating that we can conclude that these variable have considerable effect on lapsation of life insurance companies.

Exp (B) shows odd ratios. An amount more than 1 shows that the probability to win is more than the probability to lose, for example for age or gender variables, by increasing age, the probability of lapsation increases or male policyholders lapse more policies. We can also catch these results by considering coefficients.

1. Males do lapse more policies according to 3.792 odds ratio and coefficient of 1.333. Since females are more risk averse, according to this result, we can state that this Risk Aversion proxy has considerable effect on lapsation of life insurance policies.
2. We observe that odd ratio and coefficient related to marital status are .088 and -2.428, respectively. We can state that single policyholders are more likely to lapse their life insurance policies. As a result married policyholders who are more risk averse are not likely to cancel their contracts. Thus, this risk aversion proxy affects lapsation of life insurance policies, too.
3. Table 7 shows that estimated parameter for age is positive. As a result aged policyholders are more likely to lapse their life insurance policies. Athough the estimated parameter is near 0,

we can estate that age has a positive relation with lapsation of life insurance policies and amounts of odd ratio and coefficient related to this Risk Aversion proxy confirm this result.

4. We can consider clinical rate as criteria to evaluate the policyholder’s health condition or level of risk. When a policyholder faces clinical rate it means that this policyholder is not in a good health condition. We observe that coefficient and odd ratio related to clinical rate is .077 and 1.08, respectively, meaning that policyholders faced with clinical rate (risky policyholders) are more likely to lapse their life insurance contracts.
   We can test our second hypothesis by this fact that dynamic adverse selection states that policyholders with high level of risk are not likely to lapse their life insurance contracts. But, here, we obviously observe that those faced with clinical rate / who have high level of risk are more likely to lapse their life insurance contracts and it is against the theory of dynamic adverse selection.
5. We also test the effect of number of policy years / policy period and number of installments on policyholder’s decision to lapse life insurance policy. Results show that this variable has a negative effect on lapsation of life insurance contracts.
6. By referring to table 7, we conclude that the amount of premium has a positive relation with lapsation of policies. Calculated odd ratio is very high and stating that when A.P increases, policyholders are more likely to cancel their contracts. Surely, income is a very important factor here so that increasing A.P leads policyholders to lapse their contracts.
7. According to coefficient and odd ratio related to I.F.A, we can claim that by increasing initial face amount, willingness to lapse increases.

Finally we can have the following model for lapsation:

**Lapsation= 1.333*(Gender) - (2.425)*(M.S) + 0.049*(Age) + 0.077*(C.R) - (0.06)*(P.P) – (0.609)*(N.I) +3.113*(Ln(A.P))+ 1.68*(Ln(I.F.A))**

We obviously observe that the Amount of Premium is the most effective factor affecting lapsation of life insurance policies. Marital status also affects the most inversely the lapsation of policies.

# Conclusions

In this article, we investigated the effects of Risk Aversion proxies on the lapsation of life insurance policies in Iran Life Insurance Market. A Binary logistic analysis is used to examine the effects of risk aversion on lapsation of life insurance policies.

Results show that lapsation of life insurance policies has a negative correlation with the risk aversion level of policyholders. Age, gender and marital status as risk aversion proxies affect lapsation of life insurance policies and the null hypothesis $\beta_i=0$ is not rejected for education.

Since individuals with low level of risk aversion (high-risk individuals) lapse their contracts more than the individuals with high level of risks, dynamic advantageous selection exists in Iran Life Insurance Market. In other words it seems that Iran Life Insurance Market faces dynamic advantageous selection situation rather than dynamic adverse selection.

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## Appendix

Table 1

| Variable | Lapsation | Factors | Percent |
|---|---|---|---|
| **Gender** | Not lapsed | Female | 42.2 |
| | | Male | 57.8 |
| | lapsed | Female | 19.0 |
| | | Male | 81.0 |
| **M. S.** | Not lapsed | Single | 29.5 |
| | | married | 70.5 |
| | lapsed | Single | 59.5 |
| | | married | 40.5 |
| **Education** | Not lapsed | Not educated | 61.6 |
| | | educated | 38.4 |
| | lapsed | Not educated | 59.5 |
| | | educated | 40.5 |

Table 2

| | | | |
|---|---|---|---|
| **Not lapsed** | **N** | **Valid** | **1000** |
| | Mean | | 25.9470 |
| | Std. Deviation | | 14.74230 |
| | Percentiles | 25 | 15.0000 |
| | | 50 | 28.0000 |
| | | 75 | 35.0000 |
| **lapsed** | N | Valid | 42 |
| | | Missing | 0 |
| | Mean | | 25.0000 |
| | Std. Deviation | | 11.15085 |
| | Percentiles | 25 | 17.7500 |
| | | 50 | 26.0000 |
| | | 75 | 32.0000 |

Table 3: Variables in the Equation

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| **Step 0** | Constant | -3.160 | .158 | 402.336 | 1 | .000 | .042 |

Table 4:Omnibus Tests of Model Coefficients

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| **Step 1** | Step | 206.277 | 9 | .000 |
| | Block | 206.277 | 9 | .000 |
| | Model | 206.277 | 9 | .000 |

**Table 5: Classification Table**

| | Observed | | Predicted | | |
|---|---|---|---|---|---|
| | | | Lapsation | | Percentage Correct |
| | | | Not lapsed | lapsed | |
| Step 1 | | Not lapsed | 983 | 7 | 99.3 |
| | | lapsed | 19 | 23 | 45.8 |
| | Overall Percentage | | | | 97.5 |

Table 6: Model Summary

| **Step1** | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| Lapsation | 144.923 | 0.181 | 0.628 |

**a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.**

Table 7

| Variables | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| **Gender** | 1.333 | .535 | 6.215 | 1 | .013 | 3.792 |
| **M.S** | -2.425 | .672 | 13.019 | 1 | .000 | .088 |
| **Age** | .049 | .022 | 4.869 | 1 | .027 | 1.050 |
| **Education** | -.134 | .486 | .076 | 1 | .783 | .875 |
| **C.R** | .077 | .031 | 6.108 | 1 | .013 | 1.080 |
| **P.P** | -.060 | .017 | 11.737 | 1 | .001 | .942 |
| **N.I** | -.609 | .122 | 24.815 | 1 | .000 | .544 |
| **Ln(A.P)** | 3.113 | .487 | 40.807 | 1 | .000 | 22.492 |
| **Ln(I.F.A)** | 1.068 | .320 | 12.209 | 1 | .000 | 2.078 |
| **Constant** | -10.235 | 2.726 | 14.095 | 1 | .000 | .000 |